Social Network Cognition: An Empirical Investigation Of Network Accuracy and Social Position

by

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ABSTRACT

Social Network Cognition: An Empirical Investigation Of Network Accuracy and Social Position

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The navigation of social relations is a central part of human life. In 1998, Robin Dunbar proposed the social brain hypothesis: brain size, particularly the neocortex, is directly related to the size and complexity of social networks of the species. This is due to the computational complexity needed for memorising relationships, and social skills necessary to manage those relationships.

There is a key research field attempting to deal with questions around understanding social networks. Embedded in a structuralist agenda, social network analysis (SNA) offers theory, concepts, mechanisms, and tools to investigate social networks. A particular subset of the field investigates how individuals encode and perceive social networks. The realisation that humans are surprisingly inaccurate about social relations around them, prompted scholars to investigate why. If understanding social environments is such an important part of human life, why do researchers observe such inaccurate perceptions. The question led to investigations into the causes of individual misperceptions of social relations, and the consequences of such distorted perceptions. In other words, what causes people to misperceive crucial social relations, and what are the effects of differentiations of perceptions for individuals and groups?

Prior work has mostly focussed on organisational contexts, which offers natural boundaries for social networks, as well as individual and group motivations for the functioning of the networks. Evidently, some individuals are more accurate than most, and a natural direction is to investigate why, and what the consequences are for these individuals. The

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literature employs a key assumption, which up to this point has been unchallenged. Inherited from the structuralist agenda, it has assumed that accuracy about the social network is the result of an individual's social position. The network structure offers the opportunities and constraints for the individual, and thus results in increased awareness of social relations from an advantageous social position.

The assumption is challenged in this thesis through highlighting evidence from a logical inconsistency between empirical findings and the proposed theoretical framework. Prior research proposes that individuals are accurate due to their position exposing them to information about social relations, a classical structuralist stance. Yet, when individuals in a formalised social position (such as organisational rank) are consistently observed to have lower acuity, the theoretical explanation cites *motivation* as antecedent, thus introducing agency into a structuralist theory. Proposing agency as an ad-hoc explanation for this finding does not offer a coherent theoretical framework. This, therefore, prompts a need for developing a more coherent theoretical framework from which to interpret the empirical findings, and guide future research.

The pure structuralist theory for social acuity is thus challenged through a critical analysis of current literature and empirical findings. Three hypotheses are developed which is tested with new and prior data. Using non-parametric tests, the hypotheses are substantiated, which prompts an elaboration of the thesis to develop a formalisation of theoretical frameworks. The implicit assumptions of prior work are formalised under *exposure theory*, which stands as a structuralist approach to social network cognition. Subsequently, a formalisation of the thesis is developed into *networking theory*, which is a contextualisation of structuration theory.

The thesis then draws increasingly broader conclusions for future research, and opens key questions about the role of cognition of social networks in a modern environment characterised by broad access to internet and social media platforms, enabling us to establish networks beyond our original capacity, as set by Dunbar.

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UITTREKSEL

Sosiale Netwerk Kognisie: 'n Empiriese Ondersoek Na Netwerk Akkuraatheid en Sosiale Posisie

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Die navigasie van sosiale verhoudings is 'n sentrale deel van die menslike lewe. In 1998 het Dunbar die sosiale breinhipotese voorgestel: breingrootte, spesifiek die neokorteks, is direk verwant aan die grootte en kompleksiteit van sosiale netwerke van die spesie. Dit is te danke aan die kompleksiteit wat benodig word vir die memorisering van verhoudings, en sosiale vaardighede wat nodig is om daardie verhoudings te bestuur.

Daar is 'n sleutel navorsingsveld wat probeer om vrae te antwoord rondom die verstaan van sosiale netwerke. Vanuit 'n strukturele agenda, bied sosiale netwerkanalise (SNA) teorie, konsepte, meganismes en instrumente om sosiale netwerke te ondersoek. 'n Spesifieke deelversameling van die veld ondersoek hoe individue sosiale netwerke waarneem en enkodeer. Die besef dat mense verrassend onakkuraat is oor sosiale verhoudings rondom hulle, het geleerdes genoop om te ondersoek in te stel na waarom dit so is. As die begrip van sosiale omgewings so 'n belangrike deel van die menslike lewe is, waarom sien ons sulke onakkurate persepsies. Die vraag het gelei tot ondersoeke na die oorsake van individuele misverstande van sosiale verhoudings en die gevolge van sulke verwronge persepsies. Met ander woorde, wat veroorsaak dat mense belangrike sosiale verhoudings misinterpreteer, en wat is die gevolge van verskille van persepsies vir individue en groepe?

Voorafgaande werk het meestal gefokus op organisatoriese kontekste, wat natuurlike grense bied vir sosiale netwerke, asook individuele en groepmotiewe vir die funksionering van die netwerke. Dit is duidelik dat sommige individue meer akkuraat as die meerderheid

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is, en 'n natuurlike neiging, is dus, om ondersoek in te stel oor waarom dit die geval is, en wat die gevolge vir hierdie individue is. Die literatuur gebruik 'n belangrike veronderstelling, wat tot dusver onbetwis is. As 'n resultaat van die strukturele agenda, word dit aanvaar dat akkuraatheid oor die sosiale netwerk die gevolg is van 'n individu se sosiale posisie. Die netwerkstruktuur bied geleenthede en beperkings vir die individu, en sodoende lei dit tot toenemende bewustheid van sosiale verhoudings vanuit 'n voordelige sosiale posisie.

Hierdie aanname word hier uitgedaag deur bewyse van 'n logiese inkonsekwentheid tussen empiriese bevindinge en die voorgestelde teoretiese raamwerk uit te lig. Vorige navorsing stel voor dat individue akkuraat is weens hul posisie wat hul blootstel aan inligting oor sosiale verhoudings. Hierdie is 'n klassieke strukturele siening. Tog, wanneer individue in 'n geformaliseerde sosiale posisie (soos organisatoriese rang) konsekwent waargeneem word om laer akkuraatheid te hê, benoem die teoretiese verduideliking *motivering* as antesedent, dus die bekendstelling van agentskap binne 'n strukturele teorie. Die voorlegging van agentskap as 'n *ad hoc* verklaring vir hierdie bevinding, bied nie 'n samehangende teoretiese raamwerk nie. Dit lei dus na 'n behoefte aan die ontwikkeling van 'n meer samehangende teoretiese raamwerk om die empiriese bevindings te interpreteer en toekomstige navorsing daarop toe te spits.

Die suiwer strukturele teorie vir sosiale akkuraatheid word dus uitgedaag deur 'n kritiese analise van huidige literatuur en empiriese bevindinge. 'n Model word ontwikkel, bestaande uit drie strukturele hipoteses, wat met nuwe en vorige data beproef word. Met behulp van nie-parametriese toetse, word die model gestaaf, wat in die uitwerking van die proefskrif vereis om 'n formalisering van die teoretiese raamwerke te ontwikkel. Die implisiete aannames van vorige werk word geformaliseer onder *blootstellingsteorie*, wat as 'n strukturele benadering tot sosiale netwerkkognisie staan. Vervolgens word 'n formalisering van die sentrale proefskrif ontwikkel in *netwerk teorie*, wat 'n kontekstualisering van struktureringsteorie is.

Die proefskrif trek dermate toenemend breër gevolgtrekkings vir toekomstige navorsing en ontwikkel belangrike vrae oor die rol van kognisie van sosiale netwerke in 'n moderne omgewing, wat gekenmerk word deur breë toegang tot internet en sosiale media-platforms. Hierdie blootstellings stel ons in staat om netwerke buite ons oorspronklike kapasiteit, soos beoog deur Dunbar, te vestig .

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CHAPTER 1

INTRODUCTION

Social relationships are changing, and technologies such as web 2.0, social media, and mobile phones are receiving considerable attention as the cause for many of the changes (Wellman, Haase, Witte and Hampton, 2001). This only a continuation of a long arc of changes in society, driven by incremental technological developments. History witnessed large jumps in technological advancements that increased the learning curve for human social abilities (Rainie and Wellman, 2012). Developments including the printing press, steam engine, telegraph, internet, and mobile computing provide clear examples of how technological developments pushed the limits of social life. With faster travel times came larger and more dispersed networks, and the telegraph separated time and space of social interaction, enabling individuals to communicate instantaneously without having to travel. Already in 1929, Karinthy called attention to the change of social connections in his series, "*Everything is changing*":

> "*Let me put it this way: Planet Earth has never been as tiny as it is now. It shrunk - relatively speaking of course - due to the quickening pulse of both physical and verbal communication. This topic has come up before, but we had never framed it quite this way. We never talked about the fact that anyone on Earth, at my or anyone's will, can now learn in just a few minutes what I think or do, and what I want or what I would like to do. If I wanted to convince myself of the above fact: in [a] couple of days I could be - Hocus pocus! - where I want to be.*"[1] (Karinthy, 1929, p. 21)

Credited with the idea that led to six-degrees of separation, Karinthy (1929) expresses the idea through an exchange between characters in "*Chain-links*":

> "*We should select any person from the 1.5 billion inhabitants of the Earth - anyone, anywhere at all. He bet us that, using no more than five individuals, one of whom is a personal acquaintance, he could contact the selected individual using nothing except the network of personal acquaintances.*" (Karinthy, 1929, p. 22)

[1] Square brackets not original.

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Milgram (1967) was first to empirically confirm the intuition, by observing that the separation between people averages six degrees. However, the internet, web 2.0, and mobile phones now make it possible to establish larger networks, which decreases the degrees of separation. In the past, moving from one city to another meant that one needed to re-establish social ties at the destination, and sever old ones from the old location.[2] Now people can maintain much larger and much more diverse social networks, which trace the process of their lives, from home town, university cohort, adult home, colleagues, and hobby clubs. Without much effort, people can retain and invest an expanded social network. In 2012 Backstrom *et al.* found that the average distance between people, at least in their digital friendship networks, averages around four. In 2016, researchers from Facebook Research reported an even lower average the number of intermediaries at 3.57. This depicts a shrinking world, while personal networks become bigger.

Personal social networks have, therefore, grown dramatically from the small geographically restricted social networks, to unrestricted global networks. The cognitive limitations in handling social complexity becomes problematic. Consider the cost implications to maintaining such numerous social relations: the time needed, cognitive capacity occupied, and required engagement in social grooming to maintain a larger network. Unsurprisingly, biology finds limits to social circles, where the size of the brain dictates the limits for social complexity (Dunbar, 1998; Tamarit, Cuesta, Dunbar and Sánchez, 2018). Humans have a particular ability for increasing their own capacity through technological advancement, such as the steam engine, and such technological developments are not restricted to physical inventions. Examples of abstract inventions to improve social capacity include democracy, and the nation state. Both are complex systems, which enable large and diverse groups to co-ordinate and collaborate.

These systems have limits, and these limits are surfacing more frequently in modern society, where new technologies drastically increase social complexity with which the individual needs to deal. Social media, first heralded as the great democratic information tool, has also introduced disruptive events within democratic systems. Social media was believed to connect society and ultimately create a global *netizen* of everyone (Ferguson, 2017).[3] Sun-

[2]Indeed, Watts and Strogatz (1998) used this intuition, from his own experience as an Australian in the US, to come up with the mathematical model for small-world networks.

[3]A netizen is a colloquial term used to depict a person that habitually uses the internet active. In the spirit of Ferguson (2017), it envisions a participant of the decentralised global network of citizens, using the internet to promote access to information, where all citizens are equal.

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stein (2017), for example, highlights the *daily me* concept, and bemoans the early utopian visions of connected individuals, turning out more problematic than originally envisioned.[4]

These new platforms challenge the fundamental limits of cognitive capacity to deal with social complexity. It is, therefore, timeous to investigate how people encode, understand and utilise their social networks. To develop an understanding of how people build and become aware of their social networks would develop foundational work to lead to a better understanding of larger scale issues. For instance, members of social media platforms have access to global information networks. It is reasonable to expect that the discerning social agent would curate a network, which would improve their lot. However, as frequently observed (see Del Vicario *et al.*, 2016; Sunstein, 2017), counter productively, people tend to haphazardly curate information sources, which do not substantively benefit them. Modern phenomenon such as fake news and online echo chambers are not new, but they are disruptive to the vision of an interconnected networked society.

1.1 Research Problem

Before understanding human perception and engagement in digital networks, there is a large body of work, which deals with social networks in the *analogue* domain.[5] This area of research is called social network analysis (SNA), and has been in development since the 1930's. The field experienced a resurgence due to the availability of data and new research context of the network society, which provided impetus for both understanding networks in general, and how social networks work (Wellman, 2000).

SNA was developed from structuralist sociological thought, particularly from Durkheim and Simmel, and was almost independently re-established outside the field in the early 2000's among a group of physicists (Freeman, 2004). Structuralists highlighted the role of social structure in society, and motivated why many observations of individual behaviour could be ascribed to structural features. It is often repeated that structure both enables and constrains an individual's agency, which placed SNA, with its mathematical rigour and structural inclination, in a favourable position to develop into a productive research field (Borgatti and Halgin, 2011*b*). With the emergence of electronically mediated social net-

[4]The daily, as a concept, describes how people can, using technology, curate a personalised information environment, thus representing a daily newspaper curated for *me*.

[5]What is meant by analogue is simply to contrast to digital social networks. The analogue domain is, therefore, personal social networks independent of digital channels, such as the internet, email or social media.

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works, which provided unprecedented network datasets, the field became a key research agenda for investigating and understanding modern phenomena from a network perspective.

The influence of the structuralist perspective among network theorists encouraged many researchers to emphasise the value and benefit over individualist approaches to investigate social phenomena. However, in the 1970's a series of papers brought to light an interesting issue (Killworth and Bernard, 1976, 1979). They highlighted that respondents of social network data is hardly ever accurate about social relations. The findings have wide repercussions. First, it creates questions of validity of data used in SNA, since many researchers rely on the reports of social relations by respondents. Second, if the questionnaire instruments are valid, it is a concerning finding that individuals are inaccurate about social relations and interactions. However, in reaction to these studies, many researchers investigated the phenomenon, and found that people are not randomly inaccurate, but rather make systematic errors in their judgement of social relations (Freeman, Romney and Freeman, 1987). This paints a picture of a social agent faced with cognitive limitations in dealing with social complexity.

This sparked a spurt of research into these cognitive limitations, and how people cognitively perceive social networks (Brands, 2013). This line of research can be designated as social network cognition analysis (SNCA), which investigates the antecedents and consequences of individual and group perception of social relations. This line of research reintroduced the purposive individual back into the conversation, which was previously dominated by the structuralist perspective (Kilduff and Krackhardt, 1994). This reintroduction initiated a reconsideration of the structure-agency debate, which has been a central point of contention in the field (Tasselli, Kilduff and Menges, 2015).

A final key consideration, before the problem is formally outlined, is the concept of advantage in social networks. A productive research agenda in SNA has been the investigation of key players, attempting to measure, predict and understand advantaged positions in the network (Burt, Kilduff and Tasselli, 2013). Individuals who are considered *central*, are thought to have advantages over those that are less central (Borgatti, 2006). Centrality measures are intuitive and perhaps the most notable metric to be produced from the field. It is also the most productive in predicting features of a network and individuals. Centrality is particularly linked to individual advantages in the network (Burt *et al.*, 2013).

Consider the intuitive relation between centrality and individual advantage. The same

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intuition would lead the researcher to investigate whether cognition, regardless of accuracy, could be a measure that relates to advantages to such an individual. Indeed, early research, after overcoming the need to explain that respondents are not incapable of reporting social relations, focussed on identifying the value of particular social cognitions, and specifically the advantages linked to accurate cognitions (Brands, 2013). Accurate cognitions are linked to multiple advantages, such as promotions (Marineau, 2017), power (Simpson and Borch, 2005), and leadership (Balkundi and Kilduff, 2006).

It is a natural assumption for researchers to link centrality and accurate social cognition. However, the manner in which it is linked is the problem. Researchers who attempted to link social position and acuity, used a structuralist assumption to guide the research (see Casciaro, 1998; Grippa and Gloor, 2009; Krackhardt, 1987*a*). Accordingly, empirical results suggest that people are more accurate about their social networks, due to advantages gained through their position in the social network. It is the proposition in this thesis, that the theoretical development of cognition research would be better investigated if the assumption takes a more nuanced approach to the interplay between agency (cognition) and structure (social position). It is thus forwarded that it is indeed accuracy, which predicts position.

1.2 Research Question

In the light of the above outlined problem, the first research question of the thesis is:

> What is the context of the taken-for-granted structuralist assumption of cognition, and how could it be addressed?

To investigate this, Chapter 2 to Chapter 5 threads the line of the thesis through first introducing the reader to the relevant literature on SNA, with a particular focus on the key concepts and developing an appreciation for the structuralist agenda within the field. Chapter 3 will continue this thread through a literature review of a sub-field, SNCA, which investigates human cognition of networks. Chapter 3 is also included to comment on the structuralist agenda and how it has been preserved within the reviewed literature. At the conclusion of Chapter 3, the problematic stated in the previous section should be clear, along with a proposal of how the reversal of assumption could be addressed. Dependent on the conclusion of Chapter 3, the following research question can be highlighted:

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> How can the assumption of direction of causality between social network cognition and social network position be reversed?

To develop a systematic methodology to address the second question, Chapter 4 will present an exposition of methods available to analyse social network cognition, and any particular methodological considerations that have surfaced at the conclusion of Chapter 3. The executed methodology and results will subsequently be reported in Chapter 5.

Continuing the expected thread of the thesis, Chapter 6 will expand on the findings. The guiding question for the chapter is:

> What are the implications of the empirical findings, and would it align with the theoretical lens used in prior literature?

Dependent on the findings, the relevant literature should be reviewed in concordance. If the reversal of the findings can be empirically confirmed, the chapter should offer an expanded discussion on the implications for the theoretical lens employed by prior research. It is also reasonable to attempt to propose a more congruent theoretical lens to bind the empirical findings. If the reversal is not confirmed, it necessitates a critical reflection of the proposed thesis.

1.3 Chapter Breakdown

As a guide, this section will preface the thesis by outlining each chapter, with particular attention to the objective of each, while providing linking thoughts between each.

1.3.1 Part I

The current chapter does not offer an extensive literature review, but rather establishes a thread through the research context and identified problem. For this reason, the proper literature review is divided into two chapters: Chapters 2 and 3. SNA is often proposed as a distinct paradigm compared to the traditional research agendas, and would, therefore, require a more extensive literature review, considering that the reader might not be familiar with the field. Thus, Chapter 2 is presented as a more thorough treatment of the relevant literature and research context. Key emphasis is placed on the historical development and structuralist agenda, which should offer the reader a means to appreciate the development

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of the field and its structuralist roots. Chapter 3 is an extension to the literature reviewed in Chapter 2, but the focus is on the problematisation of general SNA literature—which established the sub-field—and the particular research problem identified in this thesis.

1.3.2 Part II

With the problem defined and contextualised, this part of the thesis aims to offer an overview of methodological means, and actual choices performed to address the problem. SNA, along with SNCA, are widely characterised by the methodological core. Indeed, many argue that it is merely method, and not a distinct theoretical lens (see Borgatti, Mehra, Brass and Labianca, 2009). The field is, therefore, methodologically dense, which requires an extensive review of applicable methods to investigate the identified problem. For this reason, the methodology for this thesis is divided into a review of available methods (Chapter 4), and the executed methodology and findings for this thesis Chapter 5.

1.3.3 Part III

The findings from Chapter 5, will lead to an extended discussion about the implications for the theoretical lens employed by this thesis and prior literature. Therefore, Chapter 6 would offer an extended conclusion to the thesis by drawing wider implications in the reviewed literature in Chapter 2 and problematisation introduced in Chapter 3. Finally, Chapter 7 offers a final thread through the whole thesis by reviewing the original objectives and findings of each chapter.

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PART I

THEORETICAL BACKGROUND & LITERATURE REVIEW

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CHAPTER 2

SOCIAL NETWORK ANALYSIS

In order to understand how people think of their social environment it requires a theoretical grounding, conceptual representation and regime of empirical measurement for such social environments. Social network analysis (SNA) satisfies these requirements. This chapter thus acquaints the reader to the field, with particular focus on the historical development. The field is in its early productive stages, and readers might appreciate a wholesome contextualisation of the field.

After reading this chapter, the reader should be comfortable with the intellectual merits, key players and core concepts which identify SNA as necessary and significant in the investigation the problem highlighted in Chapter 1. It goes without saying, those familiar with the field could read this chapter as a refresher, and a focusing effort on the particular interests carried through this thesis.

2.1 Introduction

The discussion on social network analysis (SNA) starts with the brief, and obligatory, nod to the origins of the field. The section starts with the original study by Moreno on runaway schoolgirls, and progresses to the development of sociometric data and the branches found today. The next section of this chapter then outlines what makes SNA significantly different from general approaches in sociology. The final two sections highlight two central and recurring themes within this thesis: the differentiation between the architecture and flow models; and the central agency-structure debate.

2.2 Background of Social Network Analysis

Pinpointing the start of Social Network Analysis is an easy prospect due to various scholars reiterating the lineage (Berkowitz, 1982; Burt *et al.*, 2013; Freeman, 2004; Scott, 2000; Wasserman and Faust, 1994). It is challenging keeping track of the branches produced since

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the popularisation of the field after the turn of the millennium. It is further complicated because the field was independently replicated outside of social sciences by a group of physicists. The next sections outline the historical and theoretical context of the field, staring with *the origins* and subsequently exploring *the boom*.

2.2.1 The Origins: Where did it start?

To trace back to the origins of SNA is, according to some (see Scott, 2000), a complicated but easy narrative. However, as Freeman (2004) discovered, surprisingly to his own admission (Freeman, 2004, p. 159-167), the lineage is more complicated. A comprehensive review of the origins of the field is unnecessary for the purposes of this thesis, but the conceptual grounding of the field is highlighted by taking a brief look at the development.

At first, it seems as there are two ways to trace the development of SNA. The one highlights the incipience in a particular study by Jacob Moreno, the other points to coalescence of different fields. The former takes a deterministic stance and the latter a more emergent view. Neither is favoured and both are embedded in historical reality, but it confuses the academic about the narrative to follow. The former traces the routes of SNA as a field and practice, whereas the latter traces the emergence of the field as distinct within the context of academic thought. It is a difficult procedure and excessive for this thesis to separate or merge the two. A pragmatic approach is favoured by relying on Freeman (2004) and Berkowitz (1982), who jointly offer an almost exhaustive treatment of the historical development.

Those concerned with a review of SNA in its contemporary form tend to point to the research of Jacob Moreno on the Hudson School runaways. The influential part of Moreno's work was the sociogram, an early form of social network diagram, which captured the imagination of scholars in the field. With Moreno credited as the father of the sociogram, reviewers further attribute the theoretical conception of SNA to Georg Simmel. Both attributions are wholly accurate, given certain delineation. However, as Freeman (2004) shows, there are earlier references to the structural perspective in sociology from Auguste Comte. Freeman (2004, p. 3) reaches this point by using a set of characteristics of modern SNA to interpret older research traditions as to the fit within this structural *paradigm*.[1] These characteristics are:

[1] Freeman (2004, p. 3) refers to structuralism as a paradigm.

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- Social network analysis is motivated by a structural intuition based on ties linking individuals;
- It is grounded in systematic empirical data;
- It draws heavily on graphic imagery; and
- It relies on the use of mathematical and/or computational models.

Freeman (2004) divides the history of SNA into the prehistory, the birth, the dark ages between the 1930's and 1960's, and the Harvard renaissance toward the late 60's and early 70's. The prehistory relates to various structuralist scholars in sociology and psychology originating with Comte and spreading to Sir Henry Maine, Ferdinand Tönnies, Emile Durkheim, Gustave LeBon and Georg Simmel. The birth of SNA in its modern format surrounds the work of Jacob Moreno in the 1930's. However, the succeeding three decades would see the dark ages of SNA, mostly brought on by, according to Freeman (2004), Moreno's public persona. The dark ages are characterised by steady but isolated bursts of SNA research by various institutions. The Harvard renaissance during the 1970's surrounds the work of Harrison White which made strides in formalising SNA as a distinct research agenda.

2.2.1.1 The Birth

During the time of Moreno's research, there was a parallel and independent development happening around W. Loyd Warner at Harvard (Freeman, 2004). However, Warner did not enjoy the same exposure as Moreno. In part by a collapse of the research agenda at Harvard, and in part by Moreno's limelight at Columbia University. Moreno had two key collaborators; Helen Jennings, credited with adding a systematic research regime (Freeman, 2004, p. 36), and Paul Lazarsfeld who contributed to the mathematical basis (Freeman, 2004, p. 39).

Moreno managed to establish a journal called *Sociometry* surrounding his key publication '*Who Shall Survive?*' during the 1930's. Warner lead two structural studies *Yankee City* (turning outputs between 1941 and 1959) and *Deep South* (in 1941) and was instrumental in the *General Electric studies*, well-known for Elton Mayo's Hawthorne studies (Freeman, 2004, p. 45).

With these two pockets of activity, there was enough momentum to spread the structural approach to enough researchers to keep it alive until the 1970's. Moreover, they pro-

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TABLE 2.1: *Social network research centres between 1940 and 1970.*

Place	Team Leaders	Contributions
Michigan State	Charles P. Loomis	Probability models (Katz Centrality) and he refined the sociometric approach.
	Leo Katz	
Sorbonne	Claude Lévi-Strauss	General algebraic models for kinship.
	André Weil	
Lund	Thorsten Hägerstrand	Random Graph Simulation and Diffusion.
Chicago	Nicolas Rashevsky	Mathematical Models & Neural Networks.
Columbia	Paul Lazarsfeld	Personal Influence research and produced influential students: Menzel, Katz, Blau, Coleman & Kadushin.
	Robert Merton	
Iowa State	Everett Rogers	Developed diffusion of innovation theory.
Manchester	Max Gluckman	Professed the structural perspective to influential academics: John Barnes, J. Clyde Mitchell, Elizabeth Bott, Sigfried Nadel, Edward Shils,Talcott Parsons and M. N. Srinivas.
MIT	Ithiel de Sola Pool	Precursor to the Small World experiment, later conducted by Stanley Milgram.
	Karl Wolfgang Deutsch	
	Manfred Kochen	
Syracuse	Linton C. Freeman	Community decision-making.
	Morris H. Sunshine	
Sorbonne	Claude Flament	Integration of graph theory.
Michigan	Edward Laumann	Formalising Warner's approach and training influential academics: Stephen Berkowitz, Ronald Burt, Joseph Galaskiewicz, Alden Klovdahl, David Knoke, Peter Marsden, Martina Morris, David Prensky and Philip Schumm.
Chicago	Peter Blau	Generalized the idea of balance from a
	James A. Davis	cognitive to a social structural context. Developed a series of formal models dealing with transitivity in social relations.
Amsterdam	Robert Mokken	Board interlocks research and developed a set of computer programs designed to facilitate the use of graph theory in the analyses of structural data.

duced a large amount of relational data to keep researchers occupied until the renaissance at Harvard with White. These pockets of network research are captured in Table 2.1.

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2.2.1.2 The Dark Ages

There are other notable activities during this time, requiring more than a table. Kurt Lewin was instrumental in advancing the *network perspective*[2] among various students during his time at the University of Iowa (1935-1944) and MIT's Research Centre for Group Dynamics (1945) until his sudden death in 1947. One of the notable students was Alex Bavelas, who continued research in the same fashion, and recruited R. Duncan Luce a mathematician at MIT. This collaboration (within the new Group Networks Laboratory at MIT) lead to key developments towards what is called SNA today, with all the characteristics highlighted by Freeman (2004). Their work even attracted the Nobel Laureate Herbert Simon who published a paper in the field (see Guetzkow and Simon, 1955). Dorwin Cartwright and Leon Festinger, who remained at the Group Dynamics research centre (at this point moved to Michigan University), were further able to produce valuable work. They included the mathematician Frank Harary, who helped develop the mathematical basis for *signed graphs*.[3] Thus, the Lewin group's main contribution was to put mathematics, mostly graph theory, at the centre of the research agenda (Berkowitz, 1982, p.13).

The Loomis group at Michigan State University refined the *sociometric* approach and collected a large set of relational data during the 1940's (Freeman, 2004, p.118).[4] Leo Katz went on to develop a new measure of centrality, *Katz Centrality*, in 1953 (Katz, 1953), which is closely related to *Eigenvector Centrality* and Google's *PageRank*. Lévi-Strauss and Weil's partnership produced a formal model for social network analysis and solidified kinship research during the 1950's, which found traction with other scholars, but was limited to kinship researchers (Freeman, 2004, p.118). Rashevsky & Hägerstrand each had a large impact on the development of the field of mathematical and structural progression. However, their developments remained outside of the scope of those outside of their respective fields; mathematics (Rashevsky) and social geography (Hägerstrand) (Freeman, 2004, p.119).

The Lazarsfeld-Merton Group at Columbia produced a large set of structural data and made strides in interpersonal influence research. They influenced a large group of researchers who became key figures in the field today. James S. Coleman, Elihu Katz and Her-

[2] A *network perspective* is the commonly referred to approach by researchers who choose to understand elements of a system as a network. It parallels *structuralism*, but makes use of network terminology.

[3] A signed graph is a network where each edge between nodes is either positive or negative, thus it includes a sign. This is opposed to merely a binary relation of 1 or 0.

[4] A sociometric approach is synonymous to a network approach, except perhaps that it highlights the utilisation of sociometric tools such as network plots.

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bert Menzel produced key publications in the diffusion of innovation (Coleman, Katz and Menzel, 1957; Menzel and Katz, 1955). Peter Blau developed the notion of *homophily* (Blau, 1977) leading to the concept of *Blau Space* in SNA (Mcpherson and Ranger-Moore, 1991).[5] Charles Kadushin went on to extend the concept of Simmel's social circles (Kadushin, 1966).[6]

Everett Rogers was interested in *diffusion* research and applied the structural approach after being influenced by Moreno's sociometry and Lazarsfeld's interpersonal influence data.[7] He performed ground breaking research on diffusion using this perspective (Rogers, 1962), which culminated into the concepts of the stages of adoption regularly cited today.

Max Gluckman and the 'Manchester School' professed the structural perspective due to the influence of the travelling academic Radcliffe-Brown (Freeman, 2004, p.103). The Manchester school went on to produce highly influential researchers who would lay foundations for SNA. John Barnes gathered relational data (Barnes, 1954), while Mitchell (1969) and Nadel (1957) used sociograms in their research and Bott (1971) researched social support in families.

The Pool-Kochen-Deutsch group were responsible for the inception of the *small world* notion. Pool and Kochen's work (Pool and Kochen, 1978) directly influenced Stanley Milgram, who is famous for the Milgram Experiment (Milgram, 1967)[8].

In Syracuse, Sunshine and Freeman were using the structural perspective throughout their research. They managed to pioneer work on community decision-making by applying the structural perspective, and integrated the work of Rashevsky into such social contexts. Flament took a similar step by integrating graph theory into group structure (Flament, 1963).[9] Moreover, Freeman later produced key works on *centrality* (Freeman *et al.*, 1987).[10]

[5]Homophily is the observation that similar elements of a system, or indeed a network, tend to cluster together. Consider, for example, age as a measure of similarity, or race. Blau space is similar to the homophily principle, but is particularly focussed on the flow of information over a network. Accordingly, two individuals with high Blau space distance, will unlikely interact.

[6]Simmel's social circles is the intuitive concept of an indiivual's immediate social relationship environment. A person can belong to multiple social circles—university,chess club,home-owners association—and these social circles can have varying degrees of overlap, which is at the minimum, the person belonging to all of them.

[7]Diffusion research investigates the spread of information through systems.

[8]Although the publication of Pool and Kochen (1978) is after Milgram (1967) the fugitive paper was in circulation since two decades prior (Freeman, 2004, p.150)

[9]This was a process of formally expressing notions of group structures, such as cliques, in terms of graph theoretic expressions.

[10]Centrality is a key concept in SNA, which refers to how central a particular node is in a network.

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At Michigan, Edward Laumann set out to build on Werner's work at Harvard. He, along with notable students, established scaling methods of social communities into a flexible tool used to test concepts and alternative hypothesis about the organisation of communities (Berkowitz, 1982, p.6). One such a publication by Laumann in the mid 1960's is Laumann and Guttman (1966), where he and Guttman explored the inter-organisational mobility using scaling methods. More notable, is the influence and continuity fostered by Laumann through educating influential contemporary SNA academics including Stephen Berkowitz, Ronald Burt, Joseph Galaskiewicz, David Knoke and Peter Marsden.

Toward the end of the 1960's Blau and James A. Davis worked together and Davis produced a paper (Davis, 1967) generalising the idea of *balance* (from Heider, 1946) in graph theoretic terms (from Cartwright and Harary, 1956), moving it from a cognitive to a social structural context (Freeman, 2004, p.116).[11]

In Amsterdam Robert Mokken lead an influential study with the help of Jac Anthonisse (a computer programmer) and Frans Stokman (graduate student) on interlocking directorates in the Netherlands. Their studies were strongly influenced by Katz and Lazarsfeld (1955), Rogers (1962) and Harary *et al.* (1965). They started to produce computer software (GRADAP) designed to facilitate the use of graph theory in structural data which helped to make the field more accessible and speed up data analysis (Freeman, 2004, p.140).

2.2.1.3 The Harvard Renaissance

At the same time as Blau and Davis at Chicago and Mokken at Amsterdam, Harvard enjoyed a productive push within the structural perspective, solidifying SNAs place in academics. This Harvard renaissance was initiated by Harrison White, notably due to his undergraduate course *An Introduction to Social Relations*, drawing many talented researchers to the field (Freeman, 2004, p.123). In addition, he produced a cornerstone publication on structural equivalence (Lorrain and White, 1971) with a graduate student, François Lorrain (Berkowitz, 1982, p.5). Some of his students included Peter Bearman, Phillip Bonacich, Ronald L. Breiger, Kathleen M. Carley, Ivan Chase, Mark Granovetter and Barry Wellman (Freeman, 2004, p.127). Two students in particular would end up galvanising the field into a fully recognised academic tradition. The first was Mark Granovetter, who produced a paper

[11] Balance is the concept that interaction between elements of a system could be balanced or imbalanced. To measure this, a triad of elements is considered unbalanced if there is an odd number of negative signs between the elements Harary, Norman and Cartwright (1965).

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'The Strength of Weak Ties' (Granovetter, 1973) that captured the imagination of a wide array of fields (Scott, 2000, p.34).[12] In the wake of the rising popularity, Barry Wellman was instrumental in establishing the International Network for Social Network Analysis (INSNA) in Toronto in 1977 (Freeman, 2004, p.148), which provided a central body to act as a meeting place for all structural scholars. The next section would continue from here, but place an emphasis on the popularisation of the field.

2.2.2 The Boom: When and why did it become popular?

Freeman (2004) attributes the boom of the field to four emergent factors. The first is the formalisation and institutionalisation of the field. The second is the rise of availability and power of computing for the general populace. Third is the physicists entering the field, and lastly, it is the rise of social media or 'Web 2.0'.

2.2.2.1 Institutionalisation

The institutionalisation of the field needs some background before specific events can be highlighted. As already mentioned in the previous section, academics in the field travelled between institutions and spread the influence of the structural perspective. Freeman (2004, p.136-138), initiated by this fact, tracked the movements of various notable scholars throughout the years leading up to the Harvard Renaissance. There were key movements particularly surrounding Harvard, MIT and Chicago, between 1935 and 1964.[13] This kept the perspective alive, and established a group of like-minded researchers, with ever increasing standardisation. Also notable was Radcliffe-Brown, who essentially spread the perspective globally, and created ties in the network of researchers.

With these established connections, however loose, it was possible to gather enough momentum for conferences. A list of the meetings is shown in Table A.1 in Appendix A. In 1972, H. White planned the first, which included a few researchers outside of Harvard. Next it was H. Russell Bernard, who convened separate schools in SNA at West Virginia University. Their struggle to communicate was apparent (Freeman, 2004, p.142), which prompted them to identify the need for standardisation. Forrest R. Pitts, convoked a se-

[12] As an ode to the impact of the paper,more than four decades later Granovetter was recognised as a Thomson Reuters Citation Laureate in 2014 (Thomson-Reuters, 2014), mainly due to this publication.

[13] Notable academics who constituted the movement were Warner, Deutsch, A. Davis, Festinger, Cartwright, Luce, Pool, Rappaport, Coleman, White and Laumann.

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ries of four annual meetings in Hawaii aimed at increasing the exposure of SNA. The first meeting was mostly local staff, but by the fourth (in 1997) it had grown to include a wider array of researchers (Freeman, 2004, p.143). In 1974 the International Sociological Association held its world congress, where Barry Wellman organised a one-day conference to garner international interest and build connections by taking advantage of the scale of the parent conference. According to Freeman (2004, p.144), the first major international SNA conference was held in 1975, when Bernard and Samuel Leinhardt organised the conference at Dartmouth University. The attendee list included key figures such as Cartwright and Harary (Michigan University), Mitchell and Barnes (Manchester school), Flament (Sorbonne), Davis (Chicago) and White (Harvard). In 1978, Wellman organised another conference at the University of Toronto, which attracted, similar to the Hawaii meetings, mostly local academics, but there was sufficient outsiders to build momentum. In 1979, another meeting was held at the East-West centre in Hawaii by D. Lawrence Kincaid. The aim was to pull together communication scientists and SNA scientists. Finally, in 1981 Nan Lin organised a meeting of mostly sociologists at Albany, New York.

As previously mentioned in Section 2.2.1.3, Barry Wellman established INSNA, which would play a key role in unifying the field. The idea came to Wellman, when he was travelling in Britain between 1974 and 1975, he was struck by the similarities, but also isolation of the structuralist researchers with whom he came in contact (Wellman, 2000, p.20). He eventually decided to set up INSNA as a communications platform at the University of Toronto (Wellman, 2000). He initiated a newsletter called *Connections*, which passed through various hands and ultimately became a refereed journal.

In conjunction with INSNA and Connections, Freeman initiated a formal journal in 1978 called *Social Networks* (Freeman, 2004, p.150). The objective of the journal was to establish a central source for key SNA publications. This is because, at the time, articles on the subject were scattered around without a general narrative. As an ode to this objective, the first article published was the fugitive article by Pool and Kochen (Pool and Kochen, 1978), which influenced the Milgram experiments mentioned in Section 2.2.1.2 (see Footnote 8).

With regular meetings building up throughout the 1970's and early 1980's and an official body, paired with two periodicals, the field was primed for a regular conference. This was recognised by Bernard and Alvin W. Wolfe and thus set up the annual *Sunbelt* social network conference with the help of Wellman. The first conference was held in 1981, and high travel costs lead to interest in replicating the Sunbelt in Europe biannually. The first was in

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1989, convened in the Netherlands. In 1994 the two conferences were merged. Today, this conference is the key event on the calendar within the SNA community.

With intellectual integration and communication established, another factor played a key role in the boom of SNA's popularity. The next section will discuss the increase in computing power and development of dedicated SNA software.

2.2.2.2 Computing Power

Apart from early forms of internet connecting SNA researchers as part of a study (see Freeman, 2004, p.151-153), the availability, computing power, and development of dedicated software played a major role in bringing SNA to more researchers. Wolfe (1978, p.60) argues that the field would not have been able to gain momentum without the rise in computer technology.

Up until the point were computers were not commonplace, SNA consisted of drawing small sociograms and calculating graph theoretical and algebraic metrics for network data by hand. Especially in graph theory, computers helped with the practicality of scaling methods. However, in spite of the aid of computers, SNA research was still relegated to academics with mathematical backgrounds. It was only with the development of dedicated software that researchers no longer required considerable mathematical knowledge to test their hypothesis. Moreover, larger datasets became practical to work with, which in turn encouraged the gathering of even larger datasets. It is prudent to briefly outline the key steps in the development of SNA software. A list of the key steps in the early stages of SNA software is outlined in Table 2.2.

Computer software was being developed in the late 1950's by James S. Coleman and Duncan MacRae (Coleman and Macrae, 1960), which was refined and extended by Coleman's graduate student Seymour Spilerman. They were focussed on finding groups in network data based on individual choices. Samuel Leinhardt next produced SOCPAC I in 1971, which focussed on finding triplets and pairs in social network data (Freeman, 2004, p.139). Based on their work on block-modelling, Harrison White and Gregory Heil produced BLOCKER in the same year. The next year Richard D. Alba and Myron P. Gutmann wrote a programme called SOCK, with Alba adding COMPLT later, which took another look at identifying groups in the data. In 1973, H. Russell Bernard and Peter D. Killworth, using another algorithm, wrote CATIJ to identify groups (Bernard and Killworth, 1973). Breiger, Boorman and Arabie (1975) produced CONCOR, which was another take at equiv-

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TABLE 2.2: *Social network analysis software packages.*

Date	Programme	Focus	Developers
1960	N/A	Finding groups	James S. Coleman Duncan MacRae
1966	N/A	Finding groups	Seymour Spilerman
1971	SOCPAC I	Finding triplets and pairs	Samuel Leinhardt
1971	BLOCKER	Structural Equivalence	Gregory Heil Harrison White
1971	SOCK COMPLT	Structural Equivalence	Richard D. Alba Myron P. Gutmann
1973	CATIJ	Finding groups	H. Russell Bernard Peter D. Killworth
1975	CONCOR	Structurally equivalent groups	Ronald L. Breiger Scott A. Boorman Phipps Arabie
1975	NEGOPY	Finding groups	William D. Richards
1976	BLOCKER v2.0	Structural Equivalence	Gregory Heil Harrison White
1976	STRUCTURE	Structural Equivalence	Ronald S. Burt Harrison White
1978	SONET	Graph Theoretic tools for Kinship	Stephen B. Seidman Brian L. Foster
1979	CENTER	Centrality detection	Linton C. Friedman
1981	GRADAP	Centrality detection	Robert Mokken Frans Stokman Jac M. Anthonisse
1981	COBLOC	Structural Equivalence	Peter Carrington Gregory H. Heil
1983	SONIS	General SNA application	Franz Urban Pappi Peter Kappelhoff
1983	UCINET	General SNA application	Linton C. Friedman

alence in the same line as BLOCKER, which received an update the following year. Ronald S. Burt attacked the same problem and came up with STRUCTURE (Freeman, 2004, p.139). In 1975 William D. Richards developed another group finding programme called NEGOPY.

Three years later, in 1978, Stephen B. Friedman and Brian L. Foster developed SONET, which was a collection of tools to deal with kinship relations. In 1979, Linton C. Freeman developed CENTER, which uncovered centrality measures in network data. In 1981, Robert Mokken, Frans Stokman and Jac M. Anthonisse developed a similar software package to CENTER. Peter Carrington and Gregory H. Heil developed COBLOC the same year, which aimed at uncovering group structure based on structural equivalence measures.

All these computer programmes were narrow in their scope of application, and not one

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software package could provide all these techniques in one platform. However, in 1983, two software packages were developed, SONIS and UCINET, which attempted to offer a wider use-case. Earlier programmes quickly started to reproduce this objective with STRUCTURE and GRADAP following suit (Freeman, 2004, p.141).

Today there are a number of computer programmes catering for both general and specific applications. The wide proliferation of software both fuel the development of the field, while making it accessible to a wider interest group.[14] Software packages, however, only help those interested in SNA, therefore, there are two last contributors to the general interest in SNA to cover. Firstly, the entrance of the physicists and the proliferation, and popularisation, of Web 2.0.

2.2.2.3 The Physicists

The entrance and the effect of *the physicists* is mostly documented by Freeman (2004, 2008, 2011) and Bonacich (2004). Freeman started with the physicist narrative in 2004 with a hopeful sentiment on their arrival. Bonacich (2004), in a review of two popular books by physicist entrants, made a bold statement on their lacklustre dive into SNA without due consideration for the established body of knowledge. Freeman (2008) joined in repining the entrance of the physicists, and repeats the sentiment in 2011. Although the authors seem slightly covetous, it is mostly due to their desire for the SNA body of knowledge to become unified, rather than spread across disciplines and duplicate previous developments.

Recall that there were physicists in the field between 1930 and 1990's (Kochen and White for instance), but they worked with the rest of the early SNA researchers. The entrance of the physicists was a new interest from outside the crystallising SNA discipline during the late 1990's. The interest from outside the field was sparked by an article by Duncan J. Watts, and Steven H. Strogatz in *Nature* (Watts and Strogatz, 1998). They took the idea of Milgram's experiment and modelled a network in which they observed high clustering and short path lengths leading to the small world phenomena.[15]

The conceptual lending, unfortunately, stopped there (apart from reference to small world). As already mentioned Milgram (1967) used the paper by Pool and Kochen (1978), but Watts and Strogatz failed to acknowledge, or be prompted to explore, the background

[14] One recent list of such software packages can be found in Huisman and Van Duijn (2011).

[15] Clustering is the tendency for nodes, or people, to be connected to others who are connected among themselves. Path length is a measurement of how many intermediaries it would take, on average, for any node i to reach node j.

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of the concept. It was not a fluke, as Freeman (2004, p.165-166) shows how the physicists remained separate in their citation patterns. In Figure 2.1 a clear separation is visible between the two fields. The sociologists are coloured white, the physicists black, and others are grey. Moreover, Watts (2003) admits to their somewhat deliberate ignorance:

> "Neither of us had the foggiest idea about Rappaport or Granovetter, or really anything about social networks at all [...] All this profundity of ignorance left us in something of an awkward place. We were reasonably certain that someone must have thought about this problem before, and we worried that we will waste a lot of time reinventing the wheel. But we also thought that if we went out looking for it, we might get discouraged by how much had already been done, or else trapped into thinking about the problem from the same perspective and so get stuck on the very same things that other people had [...] Telling almost nobody and reading virtually nothing, we would drop the crickets project and have a go at building some very simple models of social networks to look for features such as the small-world phenomenon."
>
> (Watts, 2003, p. 69-70)

Their article lead to 159 publications by physicists on the small world problem, which was almost exclusively a social science interest. Physicists traditionally have access to highly popular and well regarded journals such as *Nature*, *Science*, *Proceedings of the National Academy of Science*, *Reviews of Modern Physics* and *Physical Review*. The *Matthew effect* offers an additional explanation for this sudden surge in popularity (see Merton, 1968).

This nevertheless resulted in wide spread attention to the field of SNA, and Watts published two books *Small Worlds: The Dynamics of Networks Between Order and Randomness* (Watts, 1999) and *Six Degrees: The Science of a Connected Age* (Watts, 2003). *Six Degrees* reached no. 2547 in Amazon's sales rankings in 2004 (Bonacich, 2004, p. 285).[16] Watts was not the only one in this *drama*.[17] Another pair of key physicists in the field, Barabási and Albert, published an article in *Science* a year later Barabási and Albert (1999). Barábasi wrote a book in 2002 called *Linked: The New Science of Networks* (Barabási, 2002) which reached no. 4003 in Amazon's sales list (Bonacich, 2004, p. 285).[18]. Watts and Barábasi, along with

[16] No. 61009 and *Small World* is at no. 208433 as of 15 July 2015

[17] Bonacich (2004) reverts to a 'drama' narrative to report on the physicists entrance

[18] It is ranked at no. 402897 as of 15 July 2015.

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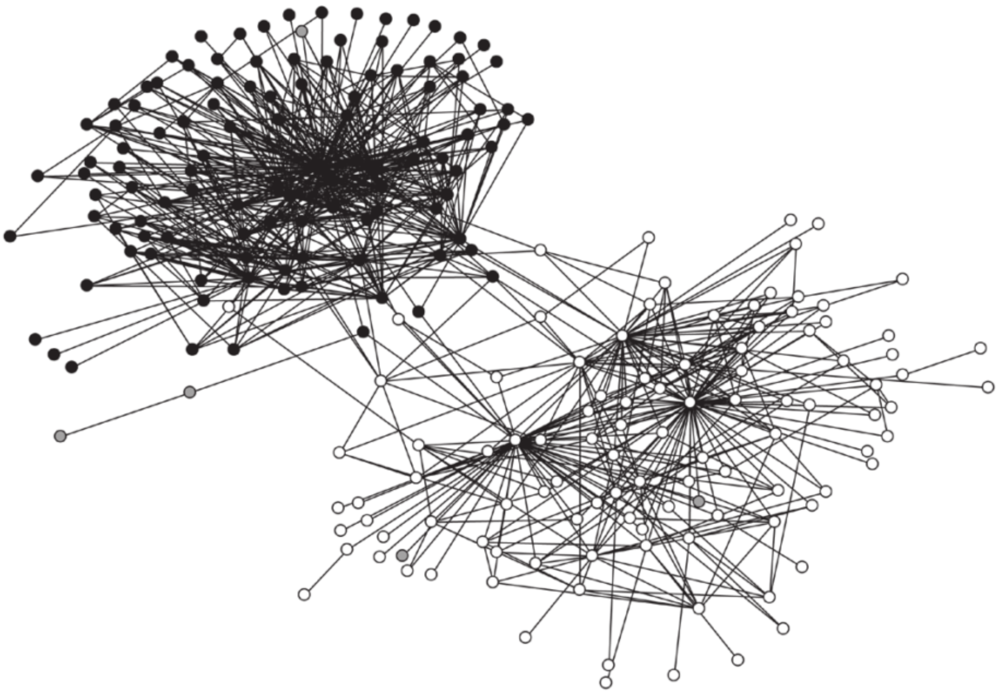
Figure 2.1: *Citation patterns in the small world literature (Freeman, 2004, p.166).*



Mark Newman (also a physicist), edited a book in 2006, *Structure and Dynamics of Networks.*, which was meant to become the key reference point for the physicist body of work in SNA.

There are two key factors distinguishing physicist research from the traditional SNA research. It does not mean these two approaches are incompatible, it merely signals a different branch. The first factor is the physicists' focus on random networks, specifically starting practically all reviews with the paper of Erdös and Rényi (1959). [19] Secondly, they argue, especially due to the rationalisation offered by Watts (2003, p. 50), that networks need to be studied as dynamic structures. This is nevertheless not the place or context to elaborate on the differences. This section is set out to understand how the entrance of the physicists played a role in popularising SNA. Some of these were highlighted above, but there is a notable contribution by the physicists that, coupled with the following section played a large role in the popularisation of SNA.

The physicists focussed their research on mostly non-social network data. Most notably, they concentrated on large data sets such as the world wide web (Albert, Jeong and Barabási, 1999), the internet (Faloutsos, Faloutsos and Faloutsos, 1999), phone calls (Aiello, Chung

[19] Similar to the way in which traditional SNA researchers habitually centres on Moreno and White.

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and Lu, 2000) and power grids (Watts and Strogatz, 1998). This established a fascination with large networks and properties such as small-world (Watts and Strogatz, 1998) and scale free (Barabási and Albert, 1999). Geared with this fascination, and fast developing measurements, the 'new' web 2.0, and especially social media would galvanise the research into the popular academic arena. The following section will discuss the rise of web 2.0, especially social media.

2.2.2.4 The Rise of Social Media

Informing the average person of one's research area as social network analysis will almost certainly elicit a response such as: '*Such as Facebook and Twitter?*' While they might be correct to some degree, this occupational hazard is an ode to the influence of *Social Media* on the field of SNA.

Boyd and Ellison (2008) published a review of social network sites (SNS) and how scholars from various fields have engaged in researching them. They define SNS as:

> "...web-based services that allow individuals to (1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view and traverse their list of connections and those made by others within the system."
>
> (Boyd and Ellison, 2008, p. 221)

These sites started surfacing for the public around 1999 with the launch of SixDegrees.com. Between the launch of SixDegrees.com and around 2002, a few sites were launched, but there was a surge in both these websites and the popularity of them towards 2007. In March 2015 Facebook achieved a user base of 1.44 billion which is by far the largest SNS. Others who reached significant numbers of users were YouTube, with 1 billion in March 2013, Google+ which had 540 million in October 2013, and Twitter with 302 million as of April 2015 (Social Media Hat, 2015).

SNA researchers now have an expansive dataset apart from just website link data, power grids and phone calls, which is primarily social. This addressed Watts' criticism of *social* network analysts' static topographies of social interaction. Now dynamic social network research has become a productive field breaking ground in diffusion and contagion studies.

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2.3 Technical Layer

At this point the technical aspects of networks can be defined and explained. There are many sources which would offer a more exhaustive introduction to the technical aspects of social networks (see Newman, 2010; Wasserman and Faust, 1994). It is important here to define a network, and offer key concepts before proceeding to the next section

2.3.1 What Is A Network?

A network is a graph, consisting of two sets of data. One is a set of *vertices* and the other a set of *edges*. Edges connect vertices, and as such must consist of two vertices.[20]

This can be mathematically represented as $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ denotes a set of g vertices $\mathcal{V} = \{v_1, v_2, \ldots, v_g\}$ and $\mathcal{E}$ denotes the ordered pairs of vertices, such as $\mathcal{E} = \{e_1, e_2, \ldots, e_L\}$. Considering a set of children ($g = 6$) Allison, Drew, Eliot, Keith, Ross and Sarah, we denote this with $\mathcal{V} = \{\text{Allison, Drew, Eliot, Keith, Ross, Sarah}\}$. Subsequently, $\mathcal{E}$ denotes the ordered pairs of v_g nodes in $\mathcal{V}$. Therefore, all nodes v_g are considered whether a link exists ($v_i \rightarrow v_j$), or not ($v_i \not\rightarrow v_j$). If a link exists it is denoted as e, so we, therefore, can have, using the above example, $L = 8 : e_1 =$ <Allison, Drew> , $e_2 =$ <Allison, Ross> , $\ldots, e_8 =$ <Sarah, Drew>. Notice that there are only eight connections out of a possible 15, assuming there can be no self referrals, and that the relationships are non-directional.[21]

Vertices and edges can take many forms. Vertices can be called points, actors or nodes, and edges can be called relations, links, ties or arcs. These are mostly different naming conventions as a result of various origin points in academic traditions.[22]

A vertex and edge can represent different things in practice. For instance, a vertex can denote individual actors (people, chimpanzees, websites) or sets of individual actors (firms, nations or species), or even proteins in organisms. Moreover, a link can denote many types of interactions between the nodes. Borgatti *et al.* (2009) provides a typical typology of ties:[23]

- Similarities
    - Location

[20] Assuming that vertices cannot connect to themselves.

[21] $\mathcal{E}$ contains at most $v(v-1)/2$ pairs given the assumptions.

[22] Arcs are sometimes reserved to represent relations that have direction.

[23] This typology has been refined in Borgatti and Lopez-Kidwell (2011), where they reduce the subcategories of social relations to role-based and cognitive/affective.

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  - Membership
  - Attribute
- Social Relations
  - Kinship
  - Role Based
  - Affective
  - Cognitive
- Interactions
- Flows

Edges is can be either *directed* or *undirected*, as well as *valued*, *signed* or *dichotomous*. Some networks can have multiple nodes, which result in *multi-mode* networks i.e individuals and firm constituting two different nodes in the same network. The inclusion of these variants of measurements necessitated an improvement on the notation conventions to accommodate for these. For instance the above expression of a graph, $\mathscr{G} = (\mathscr{V}, \mathscr{E})$, is the graph theoretic expression, but as Wasserman and Faust (1994) outlines, there is a convergence of three notation conventions that can accommodate this need. The relevant conventions are graph theoretic, algebraic and sociometric notations. These three notations provide the necessary framework (see Wasserman and Faust, 1994, p. 89-91).

Networks can be represented in multiple ways such as a matrix, an edge list, adjacency list or a coincidence matrix. Table 2.3 is an example of a simple directed network between six classmates, where an edge from one to another signals that they consider the person a friend. Figure 2.2 plots the matrix as a sociogram.

TABLE 2.3: *Matrix representation.*

$$
\begin{array}{c}
\mathscr{G}_{i,j} \\ Allison \\ Drew \\ Eliot \\ Keith \\ Ross \\ Sarah
\end{array}
\begin{array}{c}
\begin{array}{cccccc} Allison & Drew & Eliot & Keith & Ross & Sarah \end{array} \\
\begin{bmatrix}
 & 1 & 0 & 0 & 1 & 0 \\
1 & & 0 & 0 & 0 & 1 \\
0 & 0 & & 0 & 0 & 0 \\
1 & 0 & 0 & & 1 & 1 \\
0 & 0 & 1 & 0 & & 0 \\
0 & 0 & 0 & 0 & 1 &
\end{bmatrix}
\end{array}
$$

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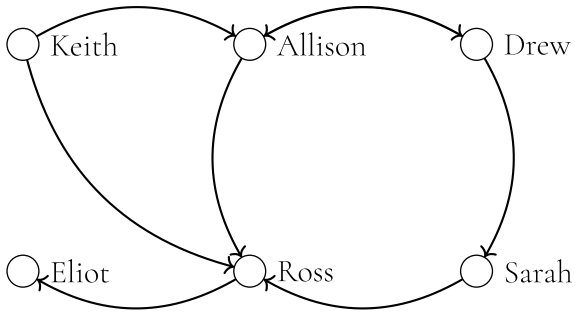

FIGURE 2.2: *Example of a small directed social network.*

2.3.1.1 Network Measures

Social relations captured in such a mathematical form makes precise measurements available. There are countless measurements of social networks, the most relevant of which will be discussed, as necessary. It is, however, prudent to highlight some here.

Social networks can be measured in two ways: on the network level, or the node level. These measurements are usually grouped into what is called graph level index (GLI) and node level index (NLI). GLIs are measurements of the network as a whole, and is useful when comparing networks. NLIs are useful when the interest is to find a particular node based on an index, such as the central node, or to compare nodes. There are methods of analysing the data which are not necessarily graph or node level indexes. Examples include census methods, such as *triad census*,[24] and structural equivalence methods. Other methods such as *community detection* are also possible, and are technically measurements or properties of the node, but these measurements are not usually regarded as NLIs since it does not index the nodes, but instead classifies them.

2.4 Central Tenets Of Social Network Analysis

SNA is difficult to define as *theory*, *model*, *perspective* or even *paradigm*. This problem is compounded because the field's name includes the word 'analysis', which suggests a methodological approach. Although the main recognisable feature of research in the field is the stark difference in methodological approach when compared to traditional sociological research, SNA is nevertheless more than a methodology or analysis technique (Borgatti *et al.*, 2009).

[24]Trad census is a census of all possible three vertex sub-graphs of the network.

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Section 2.4.1 will explore the distinction between SNA and traditional social research by expanding on three key principles.

2.4.1 What makes Social Network Analysis Different?

There are three tenets separating social network analysis from non-network research. Firstly, relations between entities matter more than the attributes of the entities themselves. Secondly, there is a distinct differentiation between groups and networks, where the latter is the focus. Lastly, relations between any two entities must be viewed in context with all other relations. The next sections will deal with these three tenets in turn.

2.4.1.1 Relations, Not Attributes

SNA research regards relations between entities more significant in explaining the behaviours of those entities. This position contrasts to the focus on attributes of entities as the key factor in explaining behaviour. An entity may constitute a person, organisation, website, or even a protein molecule.

To highlight the difference between attribute relational based approaches, two examples are offered below, one social, and one non-social. To start with the non-social, consider the highly successful PageRank search algorithm, which is the cornerstone of Google.

The key departure of the PageRank algorithm was a relational shift, i.e. the relevance of a web page to a search term is not measured based on the content of the web page (entity attribute), but rather the relation of a web page relative to other web pages. To achieve this, a web page is measured on the number of references it receives from other web pages (via links), similar to citation pattern research as by Freeman (2004, p.166) in Figure 2.1. The algorithm is as follows:

$$PR(u) = \sum_{v \in B_u} \frac{PR(v)}{L(v)} \tag{2.4.1}$$

The PageRank (PR) value for a page u is dependent on the PageRank values for each page v contained in the set B_u divided by the number $L(v)$ of links from page v.

The PageRank algorithm has changed much since its first publication, but the core idea remains. A relational method is thus more significant than content in discerning the

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importance of a web page. It is easier, quicker and more accurate, especially considering the scale of the world wide web.[25]

To move to a social example of research, which places more emphasis on relations than attributes consider the study on supply chain employees by Burt (2004). This study, amongst others, wanted to measure whether network positions (relational feature of entity) would be a better predictor for high value ideas than, for example, job level or education (entity attribute). Before details of the empirical findings are presented, first consider the argument, which lead to the research.

Burt (2004) hypothesised that an individual's position in a network, rather than their attributes, is a better predictor for success, where *success* in this case is higher value of ideas. In particular, Individuals surrounded by structural holes, as Burt propose, are more advantaged than those in more clustered positions. Figure 2.3 depicts a simple undirected network diagram of nodes a to i.

Measurements, such as degree centrality, were a step to introduce mathematical and empirical rigour to establishing the importance of a person in social settings. However, Burt added a more nuanced classification. He argues that central people are network *closers*,[26] due to their effect of causing a cluster, whereas those spanning between clusters are network *brokers*,[27] because they broker information across networks.

In Figure 2.3 there are two network closers, namely a and c, and the node spanning a structural hole is node b. Each node is advantaged based on their network position (ignoring their individual attributes). Nodes a and c have more direct access with more people and provide a unifying role in a cluster of people. This is usually beneficial for speed of communication, action and understanding among members of a cluster. Yet, b provides the opportunity to send novel information between the eastern and western clusters, this provides a form of power to b, which is not available to a and c. Node b, a broker, is able to adapt to more contexts due to the communication with different clusters. A key difference between closers and brokers is that brokers provide value for the network and themselves, whereas closers provide a benefit for the cluster.

Armed with this hunch, Burt (2004) investigated the advantage of brokerage positions. Burt (2004) tested the *idea value* of employees compared to their position of a scale on

[25]This is clearly demonstrated by the absolute dominance of Google as the world's search engine, which was the pioneer of this approach. Larry Page, the co-founder of Google, developed the algorithm.

[26]Centrality is measured on degree centrality in this case.

[27]Measured in betweenness centrality.

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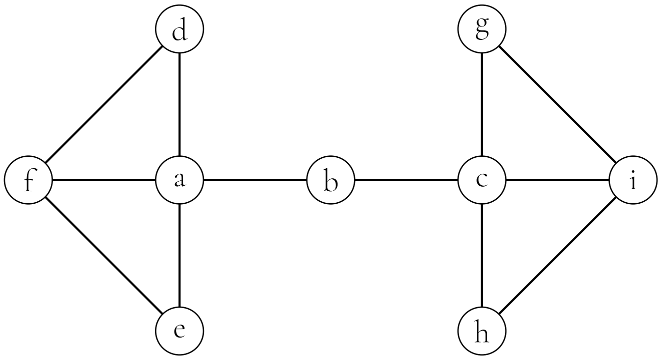

FIGURE 2.3: *Basic example of a structural hole.*

network closure. He found a strong negative non-linear relation between value of ideas and network closure i.e. the ideas of brokers were valued more than non-brokers. A positive interaction between idea value and the level of employment was found. No senior manager's idea was rejected, but within each level, network closure correlated strongly negative with idea value. He further reports no association between control variables and idea value when network closure is held constant (Burt, 2004, p. 381). These control variables were: *job rank*, *work role*, *age*, *education*, *organisation*, *geography*, and the two bias measures of *idea length* and *order* of presentation to the judges. Burt (2004, p. 383) states that "*the age and education measures of human capital pale next to the network measure of social capital.*"

In a review of network advantage research where Burt *et al.* (2013) revisited the study, they responded to the persistent thought of agency in network effects. They reiterate the strong empirical test provided by network measures for advantage, but conclude that agency dictates whether individuals capitalise on these advantages. Moreover, becoming a broker, and being able to translate and converse between fields takes cognitive effort and boundary spanning skills, which would control whether a person is found in a brokerage position in the first place. However, network advantage is observed regardless of individual attributes, similar to the content of the web pages being significant when one is obliged to choose it as the desired result, whether it is presented as relevant based on its PageRank.

2.4.1.2 Networks, Not Groups

Another principle, which distinguishes SNA, is the distinction between networks and groups, with networks as the focus. Social research, prior to the structural perspective, was concerned with identity, specifically group identity. However, from the structuralist perspec-

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tive, groups are an *a priori* definition ascribed to a collection of individuals based on a certain attribute of the individuals or group. For example, individuals can be grouped according to their membership at an organisation or department.

Networks of people are defined by a relation between individuals which establishes their inclusion. When a collection of people are the object of a study such as in an organisation, not all individuals can be grouped in the same manner. The same set of people can belong to countless networks, yet be employees of one organisation or identified in a single group. Within such a group, different individuals have different functions and levels of participation in the generic identity of the group. As Marin and Wellman (2011, p. 13) puts it: "*studying group membership as having an uniform influence on members only makes sense if membership itself is uniform*".

Network researchers nevertheless struggle with boundary specifying challenges. It is an obvious problem of where the network ends, because networks can be practically infinite. However, as Borgatti and Halgin (2011*b*) highlights, it is a natural angst in defining the boundary specifying problem, but argues that it is more of a research question problem than methodological or definition problem. If the interest is in *who trusts whom*, the organisation is of less concern in defining the boundaries. By using individual judgements of trustworthiness the network of trust relations inside or outside the organisation play a role.

Wasserman and Faust (1994, p. 14) argue that *standard* sociological perspectives use *social group* in imprecise ways .[28] SNA researchers have taken the concept of a social group and refined the interpretation. One way was to accurately define a clique and produce various generalisations of such a group structure. Other such concepts include *community*, *social circles*, and *structures of affiliation*. These mathematical definitions of different group structures promoted insights to more fundamental properties of groups such as *transitivity* or *balance*, *roles*, *status* and *position* in social groups.

Structural balance, first proposed by Fritz Heider in 1946 (see Wasserman and Faust, 1994, p. 14) was the start of a mathematical approach to describe group dynamics. Structural balance offers a mathematical interpretation and extension to the aphorisms such as: a friend of a friend must be a friend, and an enemy of an enemy must be a friend. These aphorisms express what is considered a balanced triad, if an observation deviates, the triad is said to be unbalanced and will not stay stable over time. This idea was adopted in graph

[28](Wasserman and Faust, 1994, p. 7) refers to standard sociological perspectives.

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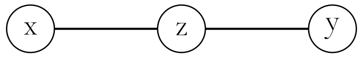

FIGURE 2.4: *Structural equivalent network to Figure 2.3.*

theory, and informed the concept of transitivity: if a is preferred to b, and b to c, a must be preferred to c.

Lorrain and White (1971) developed *structural equivalence*, which states that; if two unconnected nodes have the same neighbouring connections they are structurally equivalent and, therefore, occupy the same role or position in a network. For example, in Figure 2.3 A and C are structurally equivalent. After refining the network diagram for structural equivalence it would resemble the network in Figure 2.4. Structural equivalence is, therefore, capable of explaining similar observations between two individuals as derived from the network of relations, and not their group membership.

2.4.1.3 Relations In a Relational Context

The last key principle, in distinguishing the uniqueness of SNA, is that relations between entities are evaluated in the context of all elicited relations. A way to illustrate this is the example given by Marin and Wellman (2011). To understand relations of support, jealousy and competition between siblings, the relationship with parents need be included. In isolation, only recording relations between siblings, the dynamics of the social interaction could not be fully understood.

In general, many network measurements rely on wider patterns of relations to deduce the characteristics of a local connection. These are measurements such as degree centrality, Eigenvector centrality or structural holes.

The concept of a small-world by Watts (1999) offers an example of where a change in one relation drastically changes the dynamics of the whole network, regardless of the size of the network or local *dyadic* relations.[29] Indeed, randomly changing a dyadic relation alters the topology of the whole network by decreasing the average distance of the network.

[29] A dyad is the label for a connection between two nodes in a network. It is the smallest sub-graph possible in a network, since anything less is only considering a single node. If three nodes are in consideration, it is called a triad. Investigating sub-graphs with four or more does not have any specific labels, apart from being referred to as k sub-graph, where k is the number of nodes in consideration.

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2.5 Network Models

As a start, Georg Simmel writes:

> "A collection of human beings does not become a society because each of them has an objectively determined or subjectively impelling life-content. It becomes a society only when the vitality of these contents attains the form of reciprocal influence; only when one individual has an effect, immediate or mediate, upon another, is mere spatial aggregation or temporal succession transformed into society." (Simmel, 1971, p. 24-25)

Simmel wants to make the argument that society can only be measured on the whole, from which specifics of the individual might be inferred. One can, therefore, not infer the whole from individual measurements, and even trying to understand the individual is ignoring the whole. It is certainly impractical to measure the whole of society, but studying the networks of individuals is a step closer to this ideal.

This line of structural thinking is traced back to Claude Henri Comte de St.Simon (Comte) and Karl Marx, who first eluded an "*overarching systemic relationship that transcends individual or interpersonal relations*" (Berkowitz, 1982, p. 10). Emile Durkheim raised the idea of a set of *social facts*, which are both external to the individual consciousness and constrain their behaviour (Durkheim, 1982). Social facts can be conceived as values, cultural norms and social strata. These social facts are capable of guiding an individual's behaviour. Durkheim places the origin of these social facts not with the individual, but only within society, and therefore, the social network (Durkheim, 1982). These networks develop the social facts to which individuals in the network are subjected to. No single individual can change the facts, they can only change their association to the network which enforces them.

Berkowitz (1982) provides a distinction between socio-logistic and psycho-logistic reasoning. Within SNA the distinction is acknowledged, but operates within the former. This is where the distinction is outlined as:

> "(a) modes of reasoning which assume that the relationships between and among the elements of a social system act to set limits on or constrain the behavior of these elements and (b) ones which hold that individual or elementary forces simply 'come together' to form larger systems.
>
> (Berkowitz, 1982, p. 8)

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This reasoning is captured in the saying *"the whole is other than the sum of the parts"*, which originates from gestalt psychology.

In conclusion, there are two key concepts.

1. Collections of social actors are more (or other) than its constituent parts.
2. Individual action creates their environment, while such environment simultaneously restricts their action.

Various labels surfaced from social network theory to identify the two distinct models of how to interpret networks. Burt (1980) calls it *systems of actors* and *networks of relations*, Borgatti and Foster (2003) calls it *structuralist* and *connectionist*, Borgatti and Lopez-Kidwell (2011) settles on the *architecture* and *flow* models of network theory. The latter labels will be used here, and are expanded on in the following sections.

2.5.1 Flow Model

Adopting the flow model promotes the idea that a transfer of anything between nodes as being true (Borgatti and Lopez-Kidwell, 2011, p. 43); meaning, what is sent from one node travels on the path and reaches a destination at other nodes in more or less the same state. Borgatti and Lopez-Kidwell (2011) achieves to highlight the difference between a flow of substance and the flow of effect. An example is the distinction between the spread of gossip and being late for a meeting causing a chain of events. Gossip is spread from person to person as a unit, whereas arriving late for a meeting spreads a chain of effects, where the effects differ.

This conception of the mechanics of a social network is usually likened to pipes, and the pipes are regarded as conduits for the flow of substance. There are clear implications for this. When the pipes are longer, the flow will take longer, and if shorter it is faster. A substantive application of this assumption is in routing algorithms, such as Dijkstra (1959)'s shortest path algorithm. To find the shortest path between two nodes in a graph, traversal is assumed to take place from node to node through edges. In practice, such as navigating from city to city, some paths might be longer than others, therefore, the algorithm must take the length of the path (or pipe) into account when calculating the shortest path.

Calculating and interpreting centrality measures rely on the assumption of the model (Borgatti, 2005). Centrality measures depend on the type of resource that flows in the network. Consider the difference between gossip and money. Gossip can be duplicated,

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but money not. Money can be broken into smaller denominations, whereas gossip cannot. The utility of a centrality measure, therefore, relies on the particular resource.

There are many measurements of centrality, but the simplest measure is *degree centrality* (C_D). Degree centrality is simply a count and ranking of the number of edges incident to a vertice.

For example, given a graph as depicted in Figure 2.5, node a has a degree (number of edges) of 8, and b through i have a degree of 1. Given that $n = 9$, and assuming that self referrals are not possible (i.e a cannot link with itself), then it follows that a has a degree centrality of 1.0, and b through i have 0.125.

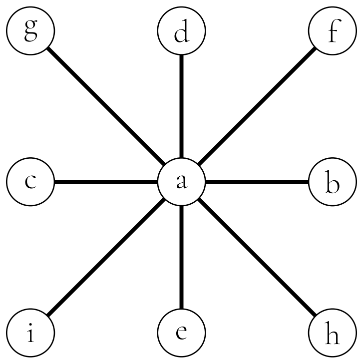

FIGURE 2.5: *Star diagram.*

This particular network would have a as the most central node in any other measurement. For instance, *betweenness centrality* (C_B) is measured by traversing all pairs of nodes i and j and establishing all possible *shortest paths*. The majority of the shortest paths would include the most central node as part of the conduit. However, in a network such as depicted in Figure 2.3 the nodes with the highest degree centrality (a and c) do not have the highest betweenness centrality (b).

Take for instance the example in Figure 2.6. In this figure it is evident that different nodes have the highest centrality depending on the measurement. For example d has the highest *eigenvector centrality*, h has the highest betweenness centrality, p or i has the highest *closeness centrality*,[30] and j has the highest degree centrality.

[30] Abraham, Hassanien and Snášel (2010, p. 30) state that p has the highest closeness centrality, they do not elaborate on their calculations, but by using the standard formula by Sabidussi (1966), computed using an algorithm developed by Brandes (2001), i is found to have the highest closeness centrality.

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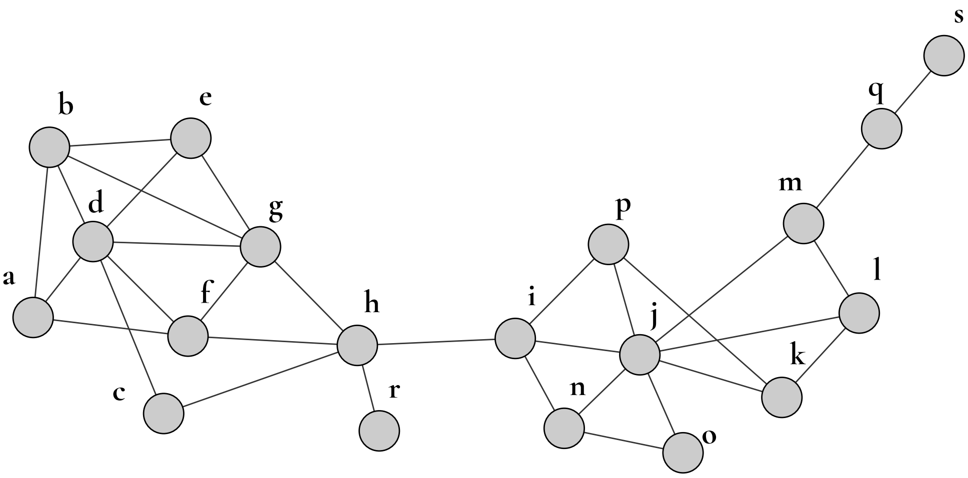

FIGURE 2.6: *Example of variability of degree measurements.*

2.5.2 Architecture Model

It is assumed that transfer will take place in the architecture model, however, the original transferred resource is not transported in its entirety (Borgatti and Lopez-Kidwell, 2011, p. 45). Theories rooted in the architecture model agree that something might travel along the conduits of network connections, but differ in the manner of the traversal. The appropriate metaphor for the architecture model would be scaffolding. Scaffolding provides the frame on which everything else is built. More specifically, these frames dictate where building is not possible. Instead of information or gossip it envisions resources such as trust or power. Power cannot flow from one person another, but it can be enforced due to a connection with a powerful *alter*. The source of power does not leave the source node, the network structure spreads the effect. The model is illustrated by comparing dyads with triads. Within a dyad, power and trust cannot flow. They either have trust or not, or one has power over the other, or not. When a third person is introduced, the power or trust within the group can be transferred through the structure of the group. The transfer can happen through mechanisms such as transitivity: Abe trusts Ben, and Ben trusts Claire, therefore, Abe would be willing to trust Claire as long as Ben does.

The architecture model is closer to the structuralist conceptualisation of behaviour. Recall the source of Durkheim's social facts: the source is not in the constituents of the social group, but is rather developed and enforced by the global structure. Thus, it is not

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an individual's explicit choice to trust in, or exert power over, another, but it is through the larger social structure that these resources become available to the individual. Social facts are not amalgamations of individual behaviour reinforcement, but are inferred from the larger structure.

The architecture model furthers a *Simmelian* view of networks, specifically regarding the importance of the triad in a network (Simmel, 1950). Simmel considers the triad a special sub-graph, since it completely changes the dyadic relation to immediately become social, and is, therefore, constitutive of social structure. However, any further additions to the network, a fourth or fifth node, does not alter the dynamics as the third. Thus, the dyadic relation, whenever embedded in social networks, must be analysed on the triadic level.

Money exchanges offer a thought experiment to contrast the two models. When borrowing money, the flow model would argue that an amount of money is transferred between parties. The money is the actual store of value that is transferred in the network. However, in the architecture model, the financial resource is not the money itself, but rather the source of the money. The capacity to lend money did not transfer from the source. Having access to a lending facility thus provides the value.

This relationship is well captured in principal-agent theory research (Eisenhardt, 1989; Rees, 1985). Similarly, transactional knowledge theory envisions *knowledge* as distributed among individuals in a network. If there was a flow of knowledge from one to another, the individuals would have to become "prodigious polymaths" to facilitate the flow (Borgatti and Lopez-Kidwell, 2011). Consider the case if it was only the borrower and lender in a network, thus a dyad. The architecture model could not account for any transfer to take place, whereas within the flow model it is perfectly reasonable to picture the money passing back-and-forth.

Borgatti and Lopez-Kidwell (2011) argues, in contrast to the flow model, that it is not the content of the flow, but the co-ordination that matters. Consider a bureaucratic chain of command. If A is superior to B, who is in turn superior to C. When A gives an order to B, it is different to an order given from B to C. What is important in this chain is, therefore, position.

Another interesting example to illustrate the contrast is to suppose three actors where A knows and trusts B, and B knows and trusts C. It can be inferred due to transitivity that A would use B's trust in C to establish initial trust. Trust, therefore, transferred from B to A, but also did not. Likewise, A's trust in C is equivalent to B's trust in C, but also

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not. Therefore, the transferred trust from B to A for C is neither a subset of B's trust, nor did it transfer, yet the same behaviour of B's trust of C in A's trust in C is observed. This can be referred to as mimetic transfer (flow model) or mimetic isomorphism (architecture model).

In conclusion, it would be prudent to view two key theoretical developments which implicitly rely on the different models. The first would be *strength of weak ties* (SWT) theory, which aligns with the flow model, and *structural hole* (SH) theory, which is based on the architecture model.

Mark Granovetter (1973) developed SWT theory. SWT famously reported the counter-intuitive finding that weak ties offer value to the network. Key to the theory is the focus on the dyad, and particularly the strength of the dyadic relation. The theory relies on a stochastic conceptualisation of flow of information in the network, and the strength of ties contributes to the dynamics of the flow. The strength of the tie, therefore, dictates the tendency to cluster in the network. A strong tie would be more present within a cluster than between. The global properties of the network is, therefore, built from the strength of ties.

Ronald Burt (2000) later developed SH theory. SH theory focuses on the triadic level to deduce whether a person spans a structural hole. A tie spanning a structural hole would tend to be a weak tie in the semantics of SWT. Structural hole theory, therefore, does not need to define and measure the strength of a tie, to deduce a bridging link between nodes.

Both theories attempt to describe the value that such a tie offers the individual and network. However, they use two different models to reach the conclusion (Borgatti and Foster, 2003). In conclusion, SWT theory places the locus of the importance of a tie on the dyadic level, and SH defines the importance of a tie based on the structure of triads.

2.6 Individual Agency Versus Network Patterning

In 2015 Tasselli *et al.* offered a review of SNA literature with a key question: Do the people make the network, or does the network make the people? This question is alludes to whether the individual, observed by researchers, is possibly a product of the social network, in which they are embedded (network makes the people), or whether the observed social network is purely a consequence of individual agency (people make the network). This section is a brief overview of the two approaches, by dividing it into network patterning and agency.

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2.6.1 Network Patterning

This approach to the study of social networks is representative of most of the conceptual and empirical work reviewed in this chapter. This is because, SNA has itself been a break from an individualistic sociological perspective towards a structural perspective that prefers to view the observed structure of society not as the consequence of individual actions, but rather the cause. Thus, in the pursuit of the impetus of social phenomena, the search should start with social network patterning.

Unable to ignore observations of individual differences, many approached the network patterning agenda by explaining the individual differences through structural measures. This led to the dominance of the notion of social position in research (Lorrain and White, 1971). In simplistic terms, social position such as centrality, dictate the observed phenomena of the person occupying such a position. A natural extension would then be that two individuals, unknown to each other, who occupy similar network positions should exhibit the same behaviour (Burt, 1982). Consequences of network patterning includes domains such as personality (Balkundi, Kilduff and Harrison, 2011) and identity (Christakis and Fowler, 2007, 2008).

The bulk of SNA literature follow this assumption, however, there is a steady increase in research, calling for the reconsideration of the individual as the genesis for social network structures. They thus call for an inclusion of the individual and the role of agency (Kilduff and Krackhardt, 1994).

2.6.2 Agency

The calls for inclusion of individuals in theorising about networks produced research from various areas. Tasselli *et al.* (2015) groups the research into genetics (e.g Burt, 2008), personality (e.g Mehra, Kilduff and Brass, Daniel, 2014*b*), demography (e.g Ingram and Morris, 2007), cognition (e.g Janicik and Larrick, 2005). Research trying to explain how genetics, personality, and demography affect social networks, can be grouped as individual differences, whereas, cognition is a category of its own. Cognition is the investigation into how individuals think of social networks, and how certain factors dictate their perceptions, and how these perceptions dictate structural realities. Consider the first research question proposed in Chapter 1:

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> What is the context of the taken for granted structuralist assumption of cognition, and how could it be addressed?

The reintroduction of agency to SNA, which is dominated by structuralist thought, highlights the context for researchers attempting to address the taken for granted assumptions of the structuralist agenda. The move, therefore, was initiated from two fronts; individual differences—such as personality and demography—and cognition research. From these fronts, a productive area would be cognition research, since it leaves space for the influence of structure, while acknowledging individual cognition as a key causal factor of social structure.

2.7 Conclusion

The chapter provides the reader with a historical and conceptual introduction to SNA. This introduction has three objectives: *First*, it offers a primer to those who are yet to encounter the relatively new field; *second*, SNA is motivated as the broad conceptual approach to investigating individual cognition of the social environment; *third*, the basic concepts are communicated, and important theoretical signals are outlined, namely the tenets and models of SNA.

The chapter depicts a rich and long history of a structuralist tradition that spans from the early days of sociology, and finds a focus in mathematical and theoretical developments. A resurgence of the field in the early 2000's saw physicists enter the fray with their rigour technical prowess. The proliferation of web 2.0 and social networking sites are increasingly expanding the limits of social networks, constantly generating new questions for research. The internet is offering a new scale for sociological inquiry and SNA is part of academia's tool-set in investigating the phenomenon.

The chapter also highlights key divisions and uncertainties within the field. Particularly, the assumptions of the network model. The confidence of the early structuralists within SNA has been receding, with an increasing number of scholars calling for a resolve of the difficult structure-agency debate (Burt, 2012; Kilduff and Krackhardt, 1994; Tasselli *et al.*, 2015). The *agency question* as Burt (2012) labels it, has either been *assumed away* or *held constant*. Some individuals take more advantage of the opportunities they are presented from the network. Usually, psycho-logistic impetus is assumed i.e., an affinity for spotting

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and taking advantage of network opportunities. This affinity is usually wrapped in a personality research. Yet, as Burt (2012) have shown, it does not offer a robust link. There is, however, a psycho-logistic approach that is amenable to structuralist thinking, namely social network cognition.

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CHAPTER 3

SOCIAL NETWORK COGNITION

> Since he came down from the trees, man has faced the problem of survival, not as an individual but as a member of a social group. His continued existence is testimony to the fact that he has succeeded in solving the problem; but the continued existence of want and misery, even in the richest of nations, is evidence that his solution has been, at best, a partial one.
>
> (Heilbroner, 1953, p. 23)

Central to human life is the navigation of social relations. In 1998, Dunbar proposed the *social brain hypothesis*. The hypothesis contends that the size of the brain is directly related to the size and complexity of social networks of the species. The motivation for this mechanism is due to the computational complexity needed for memorising relationships, and the social skills necessary to manage those relationships. In organisations the situation might be amplified, since people need to collaborate in extra-social structures, such as hierarchies, where individuals compete, implicit or explicit, for some gain or advancement. How people deal with the social complexities in organisations is, therefore, a key research agenda.

3.1 Introduction

A promising field to inform the investigation is cognitive social structure (CSS) research. CSS research is elsewhere referred to as "cognition" (Tasselli *et al.*, 2015), "social cognition" (Borgatti and Foster, 2003), or "network cognition" (Dessí, Gallo and Goyal, 2016). CSS is also the label given to a data-structure used to investigate how individuals perceive networks.

To avoid confusion, the labels need to be defined before proceeding. Social Network Cognition (SNC) is the preferred label for how individuals perceive, or cognitively represent, social networks. The analysis of, or investigation into, SNC can be labelled Social Network Cognition Analysis (SNCA).

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The previous chapter introduced the broader field of SNA. SNCA is a sub-field for which Brands (2013, p. S82) offers a distinction:

> *"...whereas SNA focuses on the actual configuration of ties surrounding individuals, CSS research describes these patterns of interactions as perceived by individuals. Thus, rather than focusing on a single network of relationships, CSS research examines social networks as viewed from each members' idiosyncratic vantage point."*[1]

SNCA evolved out of a critique on SNA penned by Peter Killworth and Russell Bernard in five articles, known as the *BKS* studies, between 1976 and 1982 (Bernard and Killworth, 1977; Bernard, Killworth and Sailer, 1979, 1982; Killworth and Bernard, 1976, 1979).[2] In 1987*a*, Krackhardt (1987*a*) responded to the critique that lead to the development of SNCA. The next section will explore the BKS critique and response by Krackhardt in more detail.

3.2 The Critique of SNA and Birth of CSS

In 1976, Killworth and Bernard raised the issue of respondent accuracy in social network data. They showed that when informants' report of communication are compared to their actual communication behaviour, the two have little relation. Killworth and Bernard (1976, p. 269) state:

> *"If an informant claimed to have communicated with some person 'the most frequently' then, in fact, he communicated with that person between first and fourth most frequently only 52% of the time"*

In a follow-up study, Bernard and Killworth (1977) confirmed the results of Killworth and Bernard (1976). They again observed poor performance when recalling communications, when compared to their actual observed behaviour. They expanded the study and found an insignificant improvement in recall when compared to the prediction of communication frequency by respondents. Allowing respondents to keep communication logs did

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[1]As explained above, CSS is also the label of a particular social network data structure, Brands' use of CSS here is equivalent to SNCA.

[2]The acronym is based on the last names of the authors; Bernard, Killworth, and Sailer. It was coined by Krackhardt (1987*a*).

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not aid in improving their accuracy. Lastly, they found respondents' confidence in their accuracy was insignificant.

Two years later, the third paper expanded the critique by focussing on the structural accuracy of the respondents from the previous datasets. They found that "*If cognitive and behavioural triads are compared, triad by triad, then there is virtually no agreement between them*" (Killworth and Bernard, 1979, p. 19).

The fourth paper changed the level of analysis from triads to cliques. They wanted to know whether cliques, derived from cognitive data, can be used as proxies for behavioural data clique structures. They found no significant relationship (Bernard *et al.*, 1979, p. 191).

The last of the BKS papers ended by asking whether time influences the accuracy of cognitive social network recall, when compared to behavioural observations. Time had no role in improving the low accuracy, but they did, however, conceded one positive for individual cognition of social structures: "*although the informants did not know with whom they communicated, the informants en masse seemed to know certain broad facts about the communication pattern*" (Bernard *et al.*, 1982, p. 30).

This concession from the BKS authors offered the first clue for Krackhardt (1987*a*), who took the critique's basic assumptions and questioned the objectives. Krackhardt (1987*a*, p. 110) addresses the assumption as:

> "*The Premise behind all these arguments—a premise declared by the use of the word 'accuracy'— is that recall is being used as a surrogate for or measure of behavior. There are two alternate ways of looking at this 'problem', based on different premises or theories, that eliminate the BKS studies findings as a 'problem' and open new avenues for approaching the study of networks.*"

There are two alternate ways. *First*, recall distortion can be due to cognitive constraints of the individual and their context that results in the use of heuristics. Factors such as recency, frequency, and importance of interaction, shape mental models of interaction patterns. These mental models serve complex cognitive processes that are not readily suited to compare to observations and equate deviations to errors. For instance, Smith, Menon and Thompson (2012) showed how respondents activate different networks depending on their level of perceived job threat. Mental representations of social networks are sensitive to contextual factors, especially considering the complexities of network patterns.

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The *second* is to investigate the varied cognitive network constructs independent of observed behaviour. Here, individual cognitive constructs are compared with of other respondents in the network. Krackhardt (1987*a*) used this approach in developing the concept and related methodology of *cognitive social structures* (CSS).

An often repeated tenet of SNA, is that networks provide the opportunities and constraints to its constituents. Here, the same tenet is repeated, but note that these opportunities and constraints need not be real, they only need to be perceived to have an effect. This realisation offers a strong clue as to the usefulness of SNCA research in understanding network behaviour. For example, if a person is centrally located, or is positioned in a bridging role in a network, they can only effectively take advantage of the position if they have some awareness of their position. Burt *et al.* (2013) share this insight when concluding on creativity and performance advantages of network brokerage positions, they concede that brokers vary considerably in their performance. Therefore, having access to network brokerage positions does not guarantee advantages for the broker. Not being a broker does nevertheless guarantee a negligible advantage.

To further explore SNCA, three groupings divide the literature. The *first* group is concerned with methodological procedures to capture and analyse CSS. The *second* grouping is concerned with factors affecting idiosyncratic cognitive representations of social networks, thus the antecedents. The *third* group focusses on the consequences of perceived networks on individuals and whole networks. Each grouping will be explored in more detail in the following sections, starting with methodological considerations. The subsequent sections will then explore literature divided into the antecedents and consequences groups as outlined above.

3.3 Methodological Approaches

It is difficult to separate method from concept in SNCA research. It is an issue inherited from SNA. The reason is the importance of methodology to both the conceptual and theoretical development in the field.

Borgatti *et al.* (2009) highlights the critique against SNA of merely being a methodology, and proceeds to highlight major theoretical advances disguised as methodology. Any relational dataset can be analysed with the same methods, whether it is social data or protein interactions. For example, closeness centrality can both be a measure of popularity in

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a social network, or a measure of single point of failure in an electronic network. Applying the same method in such a substantively agnostic manner creates the impression that the measure is merely a helpful methodological tool. However, as scholars such as Granovetter and Burt have shown, there is a great deal of theoretical work underlying these measures.

The same argument applies to SNCA. It is easy to confuse SNCA research as a specialised methodology within the SNA field, but as highlighted, it goes with a conceptual break from general methodologies. It is, therefore, important to first review the methodological considerations of SNCA research before we cover the antecedent and consequence literature. Central to SNCA research is the idea that respondents have unique cognitive representations of social network patterns. It, therefore, suggests that it is important to capture such nuances instead of avoiding them. The next section will discuss data collection methods that would enable the researcher to uncover such SNCs.

3.3.1 Data Collection

In a review of the literature, Brands (2013) highlights three key methods: CSS roster method, experimental methods, and visual methods. The CSS roster method, developed by Krackhardt (1987*a*), is perhaps the most widely used. There is also a growing body of experimental methods, based on the experiments developed by De Soto (1960). The visual methods are a more recent development that takes advantage of individuals' uncanny ability to interpret visual representations of social networks. They, therefore, use visual representations to elicit perceptions of social networks. The next three sections will explore each in turn.

3.3.1.1 Surveys

Surveys are a popular method to collect network data. The methodology for surveys can vary based on three parameters. *First*, respondents can be presented with a pre-compiled list of *alters*, called a roster, or they can be prompted with an open-ended question to recall alters.[3] *Second*, the network scope can span from an ego-network, to a whole network.[4]

[3] Alter and ego are terms used to describe the focal node in a network and possible other nodes. An ego is the focus, where all other nodes are considered alters. If a survey is employed, the respondent is considered the ego node, and all other individuals are thus alters of ego.

[4] An ego-network is a network that centres around a focal node. Usually an ego network is the result of the data from one respondent. A whole network is merely the assumption that the whole network of interest is captured. Thus, dependent on the assumption of the network boundary, the data could be considered to cover the whole network.

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Lastly, the study context might expect networks of respondents to overlap enabling them to be combined into a larger dataset. These three parameters would suffice to create enough context for survey methods in SNCA research. Each parameter is discussed in more detail below.

3.3.1.1.1 Roster vs Free-Recall The *roster* and *free-recall* methods are two of the more popular instruments used in social network research. A roster questionnaire presents respondents with a pre-compiled list of alters. If the researcher knows the identities of all the members of the network, or would prefer to bind the network to a specific set of individuals, a roster method is appropriate. However, when the identities are unknown, or the researcher only knows a subset of the identities and requires a response of a wider network, the free-recall method would be more appropriate. The researcher can indeed design a mixed method, where they have identified a list of alters, but offer the chance for free recall.

The free-recall method allows the respondent to populate the list of alters themselves, or they are allowed to append an original seed list of alters. An added factor to consider with free-recall, especially as related to SNCA, is that a respondent's recall ability is an added variable that needs to be taken into account. Similarly, the roster method places an *a priori* estimation on the examined network. The roster method limits respondents to the listed alters, but also provides a prompt to aid memory.

The choice of method is, therefore, reliant on the research question and context. If the context is such that the network is *stable*, such as in an organisation, then a roster method would be appropriate.[5] If the network is not stable, there is no choice but to use free-recall. Moreover, if the context is stable, and the research question is sensitive to individual recall ability, then care should be taken to either eliminate the variable by employing the roster method, or by taking it into account during the empirical process.

3.3.1.1.2 Network Scope The second parameter is the scope of the network. The scope can vary from *simple-ego*, to *ego-cognition*. Regardless of the scope, the actual survey question remains the same, the only variable is the options of alters. A simple-ego method only offers the chance to indicate the presence or absence of a relation between the respondent (i) and a direct alter (j). An extension of this would be to additionally ask for a judgement

[5] A stable network would be one where the individuals expected to constitute the network seldom change.

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of relations among a particular set of alters excluding the ego, which is the classic ego-centred scope (see Wasserman and Faust, 1994, p. 42). The scope can be further extended by additionally asking each respondent to answer the same question for their alters. Figure 3.1 illustrates these differences in scope.

3.3.1.1.3 Study Context The third parameter to consider is the context of the study. The key question for the researcher is whether there is an expectation that the respondents' networks will overlap. If so, this would offer the opportunity to compare network cognitions and would be of the same type as initially developed by Krackhardt (1987*a*). When no expectation of overlap exists, the cognitions cannot be compared directly, but can be used to compare features such as density or degree. This second scenario is usually used in experimental studies, such as the paired associate task design by De Soto (1960). In De Soto's design, there is no expectation that, or need for, the networks of respondents overlap, but the features of their cognitions can be compared.

Marcum *et al.* (2017) developed a similar classification. Figure 3.1 adapts Marcum *et al.* (2017)'s depiction. The only parameter not included in Figure 3.1 is the difference between a roster method and free-recall.

If there is no expectation of overlap between samples, and respondents are only expected to indicate a relation between themselves, and a direct alter, then a simple-ego network is generated. If the respondents are additionally asked to provide judgement on relations between their direct alters, a cognitive component is added to the data, producing an ego-centred network. The simple-ego networks can be combined to generate a whole network dataset, if responses (samples) are expected to overlap i.e., come from the same network population. If the ego-cognition method is used within this context, CSS data is generated—accordingly the original design by Krackhardt (1987*a*). From the CSS data generates the most information to interpret individual SNC outside the laboratory. Many experimental studies use the survey method, but specifically the ego-centred method, since it is less cumbersome for respondents, and they do not need the networks to overlap.

There are a few limitations to the CSS roster methodology. *First*, if the researcher attempts to gather information of overlapping networks, a single *site* needs to be identified.[6] Even thought the respondents do not have to be physically approximate, identifying a site

[6] A site would define an organisation in this case. However, a site can be any artefact that would offer an intuitive boundary for a social network. Thus, a site may be a particular meeting within an organisation, where the boundary is placed on temporal aspects of the network and not just physical.

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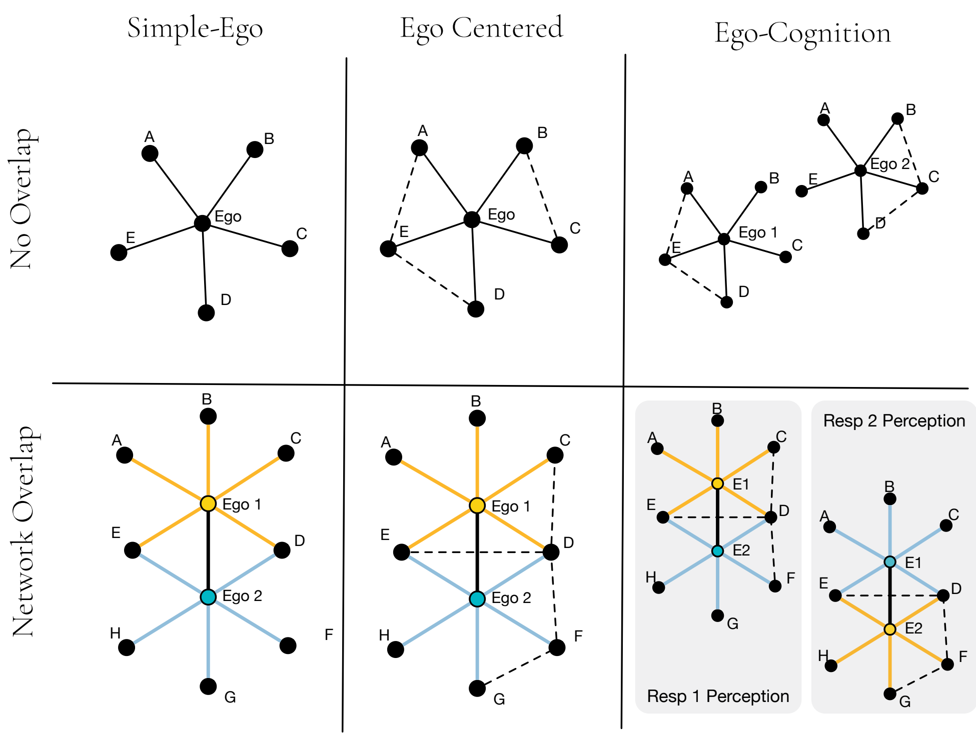

FIGURE 3.1: *The six variants of surveys adapted from* Marcum et al. (2017)*.*

means to identify a group of individuals with overlapping networks. This might be a distributed on-line network, or a social activity club. *Second*, respondents, and indeed the network, cannot be anonymous during data collection. This generates ethical, practical and logistical hurdles for researchers interested in such data. *Third*, datasets, especially full CSS, are cumbersome for respondents to answer. The larger the network, the bigger the burden for the respondent. This is especially true when using the roster method. Krackhardt (1987*a*) proposes 50 as the network size limit. Network size, therefore, carries a tax in quality of responses—the larger the network a respondent need to consider, the more they would resort to non-response or spurious responses. *Lastly*, some questions are ethically tricky to ask of the respondent, especially if they know that their alters will be answering the same questions about them. A relatively basic relational construct such as friendship can be complicated by such a research methodology.

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3.3.1.2 Experimental

Experimental methods circumvent many inherent issues of the survey method. *First*, it resolves the boundary issue. The artificial definition of the social network boundary creates the boundary issue. For instance, asking people who their friends are might limit it to their department, whereas they might have friends beyond the artificial boundary. *Second*, it controls the network structure, or *true* network and thus only focuses on systematic deviations from a particular network characteristic.[7] Various structures can, therefore, be independently controlled. For instance, the researcher can control for density, in the one treatment, and reciprocity in the next.

The paired-associate task, a popular approach, was first adapted to SNCA research by De Soto (1960) (also see De Soto and Bosley, 1962). This method asks of respondents to memorise affective relations between four fictional characters. The key objective is to see how fast people learn social structures when those structures are controlled along certain parameters. For instance, a *transitive triple* is easier to memorise than an *intransitive triple*, since it makes more logical sense to the respondent.[8]

Using this method, (De Soto, 1960) confirmed the proposition that humans build schemas close to classical mathematical properties of symmetry, transitivity, and ordering. A more recent prominent example of such an experimental approach is by Janicik and Larrick (2005), where they investigated the ability of individuals to learn simulated incomplete networks and found that those who have incomplete ego-networks, are better able to learn incomplete network schemas. The difference from De Soto and Bosley's (1962) paired-associate task to the example of Janicik and Larrick (2005), is that the latter included an ego-cognition survey with overlapping networks.[9].

Although experimental methods can avoid the inherent issues of CSS surveys, the limitations of experimental methods are still valid. The limitations include internal and external validity, especially the generalisability of the results to outside the experimental setup. Given the limitations of surveys and experiments, a more recent methodological development offers a third option that harnesses the intuition of network plots.

[7]The concept of a *true* or *criterion* network will be discussed in more detail in Section 3.6.

[8]This is due to the intuitive nature of the transitive property between three elements of a system: if $a > b$ and $b > c$ then $a > c$.

[9]See Figure 3.1.

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3.3.1.3 Visual Methods

Mehra *et al.* (2014*a*) developed the visual network scale (VNS). The VNS is a way of using an individual's visual intuition of network structures to learn about how people understand and recall social structure. The particular interest is the perception of overall network structure, since the experimental method of paired associates only considers cognition on the dyadic level.

They offer five different methods to test network cognition. The *first* is *ego-network structure*, that offers the respondent *sociograms* that indicate their supposed position in the network while varying the network along multiple parameters such as density, and changing the relative position of ego (Mehra *et al.*, 2014*a*, p. 318).[10] The respondent then indicates which network is closest to theirs in reality. The *second* method is similar, but they offer a picture of the whole-network structure. They change the emphasis from ego network to a grouping of organisation or department (Mehra *et al.*, 2014*a*, p. 318). This elicits the cognition on a network level, which has a distinct advantage over the experimental methods, and can theoretically stand as proxy for networks much larger than 50 members. The *third* method evaluate how people perceive network change by eliciting respondents' perception of network change. Another method is to elicit retrospective and prospective trajectories of networks. This is especially useful to understand how networks evolve from one particular state to the next, considering the precedent structure. Additionally, the method makes it possible to investigate preceding network patterns, and thus go backwards in cognitions of network formation. Lastly, it is difficult to know whether a respondent's cognitive slice is espoused, or a reality, but using the VNS, one can elicit network preferences. A recent application of this new methodology was by Brands, Menges and Kilduff (2015). As an experimental study, they used the VNS method instead of an ego-cognition survey method—which is usually the preferred method.

There are, therefore, three methods that can produce data for SNCA research. The following sections offer an overview of previous research employing these methods in various manners. The objectives of the research is either to explore the causes of idiosyncrasies of individual perceptions of their social networks, labelled *antecedents*, or to investigate what the *consequences* are of these cognitive patterns.

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[10] A *socigram* is a visual representation of a social network.

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3.4 Antecedents

Studies focussing on the antecedents of network perceptions investigate how differences in network perception are caused. There are multiple groupings of investigations, with some focussed on the systematic errors and cognitive biases of respondents, while others are interested in how personality influences particular perceptions. Another grouping is interested in identifying how network properties influence distortions in individual perceptions. The differences in the perceptions can be explained by the instruments used to elicit the network data from respondents (see Freeman *et al.*, 1987). Table 3.1 offers a brief outline of the literature:

To make sense of the literature, four main topics of antecedents are relevant; cognitive biases, network factors, personality, and power. Each will be expanded on in the following sections.

3.4.1 Systematic Errors and Cognitive Biases

One notable early response to the BKS studies was by Freeman *et al.* (1987), succeeding a preliminary study by Freeman and Romney (1987). The objective was to investigate how respondent recall might be more accurate on long-term significance of events. Freeman *et al.* (1987) found recall errors to be systematic, and thus not random, making these errors worth investigating. The systematic errors, the authors argued, are due to the cognitive representations created through the experience of respondents. The key takeaway is that there might be a high level of error in data collection when aiming for objective accuracy, but these same errors provide valuable information when viewed through the lens of cognitive structures of social networks, i.e how people organise their social world.

In 1992, Freeman provided more evidence of the categorical nature of social memory. He attempted to produce a theory by way of experiments that "*suggests that people impose categorical form on noncategorical [sic] affiliation patterns by a process of 'filling in the blanks'...*" (1992, p. 118). In this paper, Freeman cites the concession by the last BKS paper, also mentioned in Section 3.2, as a key motivation.

As a different approach, given the formalisation provided by Krackhardt (1987*a*), Kumbasar *et al.* (1994) showed more systematic biases in respondent's recall of their social networks. They focussed on the *centrality fallacy*,[11] which affects various cognitive products,

[11]The centrality fallacy is the cognitive bias where individuals see themselves as central in their environ-

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TABLE 3.1: *CSS antecedents literature summary.*

Article	Topic	Focus
Freeman *et al.* (1987)	Respondents are either long term general, or short term specific in their perception.	Cognitive Bias
Freeman (1992)	Cognitive network error correction affects perceptions.	Cognitive Bias
Kumbasar *et al.* (1994)	Centrality fallacy affects network perceptions.	Cognitive Bias
Casciaro (1998)	Position in the formal and informal social structure of the organization influenced accuracy of perceptions.	Personality & Network Factor
Heald *et al.* (1998)	Various individual formal and network factors influence network perception.	Network Factor
Casciaro *et al.* (1999)	Positive affectivity influenced global accuracy.	Personality
Krackhardt and Kilduff (1999)	Network distance from ego has an effect on perception.	Network Factor
Krackhardt and Kilduff (2002)	Simmelian dyads cause higher congruency.	Network Factor
Simpson and Borch (2005)	Effects of power on accuracy.	Social Role
Janicik and Larrick (2005)	Prior experiences with incomplete networks aid in learning incomplete social structures.	Cognitive bias
Flynn *et al.* (2006)	High monitor personality affects social network perception.	Personality
Kilduff *et al.* (2008)	Small world heuristic affects social network perception.	Cognitive Bias
Grippa and Gloor (2009)	Effect of network position (centrality) on accuracy.	Network Factor
Flynn *et al.* (2010)	The need for closure personality affects perception.	Personality
Simpson *et al.* (2011*b*)	Effects of power on network activation.	Social Role
Smith *et al.* (2012)	The effect of job security on network activation.	Other
Neal *et al.* (2016)	Gender, group size and homophily affects perception.	Other

and in this case, SNC. Among other findings, they illustrated how respondents consistently perceive themselves more central than the group norm.

A recent example of a study on the effect of cognitive biases intuitively illustrates how cognitive representations of observable networks have a consistently higher degree of small worldliness when compared to the actual social networks (Kilduff *et al.*, 2008).[12]

ments. An individual committing such a fallacy would falsely not believe a news or event, since they would have known about it. Westrum (1978) first described the fallacy, and later expanded it in 1982. It interestingly relies on the individual conceiving the repercussions of a network position.

[12] Smallworldliness or small worldedness as Kilduff *et al.* (2008) calls it, is a concept expressing the low average distance in a network. The phenomenon is well-known in social sciences, with the great experimenter

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Based on these studies, heuristics play a role in defining an individual's perception of their social network. Individuals employ these heuristics to reduce the complexity of social information. The result of heuristics are thus observed as systematic errors in the social network judgements of respondents, and are not merely random errors introduced by limited cognition.

3.4.2 Network Factors

Heald *et al.* (1998) identified factors that may influence the error in SNC.[13] The identified factors were divided into two categories; *formal* and *emergent*. Formal factors are objectively verifiable attributes, such as position in the formal organisational network or demographic variables. Emergent factors are informal interactions between individuals in the organisation. An example of a formal factor is a supervisor-subordinate role, whereas an informal factor can be a work-flow tie that emerges through daily interactions in the workplace.[14] Three out of the five formal factors were correlated with accuracy between co-workers, namely: being in the same department; having a supervisor-subordinate relationship; and having the same gender. Of the informal factors, two were able to predict similarity in cognitive network error. These were: task communication and acquaintanceship.

Although the list of factors in this study is not exhaustive, it does improve understanding of how position in social structure or organisational roles might affect the way social networks are perceived. This view is different from the previous section, because they do not look at factors originating from bounded rationality, but rather, social position itself. Kumbasar *et al.* (1994) investigated a similar network based factor: centrality measure. They were, however, focussed on cognitive limitations causing distortions rather than social position.

The following year, Krackhardt and Kilduff (1999) followed the same focus by investigating the effect of social distance on network perception, specifically the perception of *balance*.[15] They concluded: "*People tended to perceive relations close to and distant from themselves*

Stanley Milgram confirming the average distance between any two people to be around six. Only later did Watts (1999) provide the first mathematical models to understand small world networks.

[13] Heald *et al.* (1998) label these errors as levels of congruence.

[14] It is informative to highlight that formal and informal, in this case, closely relates to informal and formal networks as conceptualised in Section 3.7.

[15] Balance is the process of balancing triads in social relations. Balance thus illustrates the effect when A is a friend of B, and B is a friend of C, that C and A should be friends. Balanced triads originate from graph

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as more balanced than relations of intermediate distance" 1999, p. 770. Thus, individuals closer to the respondent were perceived to have more balanced relations. However, balance reduces with distance before finally again increasing. The perception of balance thus follows a non-linear relation with distance from the perceiver. A similar study by Krackhardt and Kilduff (2002) showed how dyads embedded in Simmelian ties would have similar cognitive errors in their network perceptions. In other words, these Simmelian tied dyads have a higher agreement of the informal social structure than normal dyads in an organisation.

Investigating two network measures of centrality, betweenness and degree centrality, Grippa and Gloor (2009) found that respondents who were more central, tended to underreport interactions with alters, while others' perceptions of their centrality were more accurate. In other words, people with high centrality have a higher error with their perceived networks, while still being identified correctly as central by the rest of their network.

Casciaro (1998) investigated both formal and informal network positions, similar to Grippa and Gloor (2009) and Heald *et al.* (1998), with the addition of personality factors to explain variance in network perception. Casciaro (1998) found that personality factors overall contributed significantly to explaining the variance in network accuracy, but less so compared to informal and formal network positions. The important finding for this section is that degree centrality was the best predictor of network error for both friendship and advice networks.

Network derived variables, including formal and informal social position, are, therefore, able to significantly explain variance in individual perceptions of the social network. It is important to highlight the shift in labelling the measurement of the distortions as systematic deviations, towards *error*. The concept of SNC error will be investigated in more detail in Section 3.6. However, it is prudent to briefly expand here.

Many authors, for example Freeman (1992), find patterns in individual constructions of their social networks. For instance, balanced relations change with distance from an ego, i.e, individuals tend to balance relations that are close or far to them, but have unbalanced relations at medium distance. These observations make no claim as to the accuracy of the individual's ability to cognitively represent some true network. However, in this section, and indeed the next, the narrative shifts towards accuracy. Accuraccy is intrinsically measuring individual cognition against some criteria to produce a form of cognitive performance of

theory in the work of Heider. Social distance is the distance in connections from ego. A direct friend of the respondent has distance one, and a direct contact of that friend is at distance two from ego, and so forth.

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individuals. This objective is contrasted to that of uncovering systematic patterns in the pursuit to understand cognition against measuring deviance from a criterion to relate it to other variables. This issue will be elaborated on in Section 3.6.

The next section summarises the literature investigating the role of personality in explaining variance in network perceptions.

3.4.3 Personality

Casciaro (1998) compared four personality traits to individual accuracy on both advice and friendship *relations*.[16] The considered personality traits are: extraversion; need for achievement; need for affiliation; and self-monitoring. Need for achievement displayed a moderate positive association with both advice and friendship accuracy. Need for affiliation has a positive relationship with friendship network accuracy, but a moderately negative relationship with advice network accuracy. Extraversion and self monitoring did not significantly explain variance in either network perception or accuracy.

The following year, Casciaro *et al.* (1999) performed a similar study, but focussed on one personality factor: *positive affect* (PA).[17] Additionally, they created local and global measures of network accuracy. The local measurement compares ego networks, while the global measure aggregates these networks into one and then compares each ego network to the aggregated structure. They found mixed results, with PA explaining only some variance. In summary, PA was relevant only to local accuracy in the advice network and global accuracy in the friendship network.

Seemingly independent of Casciaro (1998), Flynn *et al.* (2006) focussed on the role of personality in network perception accuracy. They focussed on the self-monitor trait, as individuals observed with this trait have an "*acuteness of perception, discernment, and understanding of social situations.*" (2006, p. 1124). They performed four studies, of which the second and fourth study are of particular interest. In the second study they used a computerised

[16]When referring to advice or friendship relations, it would be the relation between individuals that is established as a friendship relation or advice relation. This is deduced from the respondent when asking them who they consider friends. The individuals they nominate is considered as friendship relations. Relations can, therefore, have multiple dimensions for example friendship, advice, or trust. A relation between A and B might have many relations, but the researcher might only elicit two: advice and friendship. It is, therefore, reasonable to encounter statements such as 'two relational dimensions', or 'a person is accurate on the friendship relation, but not the advice relation'.

[17]Positive affect is the personality tendency of an individual to be predisposed to positive expereince. In contrast, negative affect is a predisposition to negatively interpreting the same experiences.

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exercise where respondents had to judge the nature of influence between four fictional individuals. They measured accuracy of respondents' judgements and then correlated these with each respondent's measure of the self-monitor trait. They found that respondents who measured high on the self-monitor trait, were more accurate than the low monitors, and, therefore, better able to learn social structures. In the fourth study, they found that high self-monitors were more accurate in their estimations of exchange relations among individuals in their network.

In 2010, Flynn *et al.* performed another study on the role of personality in network accuracy. In this study they focussed on the need for closure (NFC) personality construct. They define this trait as disproportionally affecting a person's need for order and aversion to ambiguity. This study relates closely to Freeman (1992), where Freeman uncovered the individual imposition of logical order on their cognitive network structure. The differentiating aspect of this study is that they uncover a personality trait that leads to the highlighted cognitive bias. They intrinsically argue that some people would fill more blanks than others dependent on their measure of NFC. They also included racial homophily as a specific outcome of NFC, as people are understood to artificially pair people based on attributes, such as race.

From the three studies, all reported in Flynn *et al.* (2010), the first is a standard social network survey, whereas the other two are controlled experimental studies. The first study found that people with high NFC were prone to overestimating friendships. Flynn *et al.* (2010) offer an interesting variant of the interpretation: high NFC individuals were less likely to identify structural holes in their network. This would be because a structural hole is established when triads are not balanced, or when local transitivity is low. These individuals would, therefore, erroneously add relations that would close any such structural holes.

The second study used an artificial network constructed by the respondents. Respondents were given photos of 16 individuals and asked to draw a social network graph consisting of these individuals known to be fellow students. The results showed high NFC individuals had a higher degree of racial homophily in their network constructions, by clustering similar race individuals in network clusters. The third study was similar to the second, but asked respondents to recreate scenes of who sat next to whom on cafeteria benches after seeing a photo of a cafeteria scene. Results again indicated that high NFC lead to racial homophily in constructing a social scene.

These studies offer a departure from previous literature by proposing individual per-

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sonality as the causal factor in perceptions of social networks. This is in contrast to network position as the causal variable. Interestingly, the studies investigating the role of personality share a key assumption that is particularly evident in Flynn *et al.* (2006) and Flynn *et al.* (2010). They assume that the motivation for the conceptualisation of the network is through personality only, whereas the motivation may be wider than personality traits. For instance, as will be discussed in Section 3.7, the environment might motivate individuals more to employ certain heuristics in the cognitive representation of their social networks, as opposed to NFC in isolation.

The next section summarises studies investigating the role of power as antecedent to network perceptions.

3.4.4 Power

In the previous sections two studies, Grippa and Gloor (2009) and Casciaro (1998), intrinsically covered the effect of power. The studies investigated the effect of formal position on network accuracy, specifically hierarchy. Casciaro (1998) found a strong negative relationship between hierarchical level and network accuracy in both advice and friendship networks. Grippa and Gloor (2009) found senior respondents under-report interactions with others when compared to sub-ordinates. The inherent assumption with equating power and hierarchy is that higher formal positions in a social network carry formal power for the occupants of those positions. These two studies equate power, at least the formal variant, to inaccurate network perceptions.

Two further studies focussed explicitly on power and its effect on network accuracy. The first is Simpson and Borch (2005), and the second is Simpson *et al.* (2011*b*). Simpson and Borch (2005) investigated the mediating role of geodesic distance of the influence of power on network accuracy. They found that if distance does not mediate accuracy, then there is no statistically significant variance in SNC accuracy between high and low power individuals. They did find that when it is mediated by distance, low-power individuals tend to have a more accurate network perception than high power individuals, especially when the distance increases. However, an increase in distance reduced the accuracy of both groups.

In another study, Simpson *et al.* (2011*b*) conducted two experiments to test the role of power on network accuracy. These experiments again found that, in general, low-power

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individuals have a more accurate network perception than their high-power counterparts. Moreover, they found that high-power individuals tend to employ more assumptions in how they construct social networks. For instance, they assumed influential (central) individuals to be more influential than they actually are. In essence, people with higher power tend to construct their social networks using more heuristics than their low-power counterparts, who spend more cognitive effort to map out their social networks.

These studies are particularly useful for the overall objective here. They offer evidence of variation of social network accuracy specifically mediated by formal position in an organisation. The general insight is that people in more powerful formal positions have a less accurate perception of the social network, compared to those occupying lower power positions. The underlying mechanism is that formal position offers benefits that nullify the need to expend cognitive effort in interpreting the social environment. Whereas lower-power positions necessitate the need for awareness of actual social network patterns. In contrast to the research placing personality as the antecedent, the motivation seems to move away from personality, towards organisational context. To extend this thought of organisational context establishing the impetus for social awareness, Smith *et al.* (2012) investigated the role of a perceived job threat and how it influences high and low status individuals' activation of their networks. They found that high status individuals, when faced with job insecurity, would activate a wider group of alters from their available network connections to prepare for losing their job. Low status individuals would activate a smaller and more intimate group of alters from their available pool of network contacts. Organisational context, and, therefore, the motivation for spending cognitive effort on social awareness, is located not necessarily in personality or network position, but in the agency and motivation of the individual. This point is further expanded on in Section 3.7.

In contrast to this section, the following review explores the consequences of an individual's cognitive distortions of their network.

3.5 Consequences

The consequences of SNC is less covered than antecedents. This is because, the initial errors found in individual cognitions of social networks were framed as a problem, prompting many to spend their efforts in explaining the antecedents of the errors. The result is a re-framing from *error* to *information*, highlighting the systematic nature of the individ-

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ual distortions that is affected by factors such as personality, network structure and social contexts.

As the need to quell the *problem* slowly relaxed, it allowed more investigation into the consequences of network perceptions. Examples of investigated consequences are power, job performance, leadership, and promotion prospects. Table 3.2 summarises the literature classified by these objectives. Three general focuses of consequences are highlighted: power, performance, and leadership.

TABLE 3.2: *CSS consequences literature summary.*

Article	Topic	Focus
Krackhardt (1990)	Accurate network perception contributes to power.	Power
Kilduff and Krackhardt (1994)	"Basking in reflected glory" effect leads to positive performance evaluations.	Performance
Balkundi and Kilduff (2006)	Thesis on network awareness accuracy as indicator of leadership.	Leadership
Ho and Sze-Sze (2009)	Expertise recognition contributes to job performance.	Performance
Simpson *et al.* (2011*a*)	Network knowledge affect use of power.	Power
Hahl *et al.* (2016)	Network knowledge asymmetry leads to structural holes and higher returns for brokers.	Performance
Marineau (2017)	Trust network awareness improves promotion prospects.	Performance

3.5.1 Power

Krackhardt (1990) was the first to attempt a link between cognitive accuracy and power, by asking whether accuracy can itself be a form of power. Krackhardt found that formal position accounts for the bulk (43%) of variance in perception of power, while centrality in advice and friendship networks accounts for another 17% variance, with advice centrality contributing the least. The focus variable—*network accuracy*—accounted for another 8.2% variance, but this time only when related to the advice network and not the friendship network. The key finding is that cognitive accuracy did significantly correlate with power, but only with accuracy of the advice network and not friendship. It also explains the least variance compared to formal and informal positions. Cognitive accuracy of the advice network did not co-vary with formal authority and is, therefore, still significant in explaining

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power. This is in contrast to advice network centrality correlating with formal authority that explains high variance in network accuracy. Friendship network centrality, which does not correlate with formal authority, accounts for little variance. There is, therefore, real evidence that perceptions of social networks might have substantive consequences for individuals.

The sentiment of Krackhardt (1990) is echoed in the experiments by Simpson *et al.* (2011*b*) and Simpson and Borch (2005) who found that low-power individuals tend to have better cognitive network accuracy compared to high power individuals. Important to note, however, is that Simpson *et al.* (2011*b*) explicitly assume that an individual's network position dictates their social network accuracy, whereas Krackhardt (1990) argues that accuracy itself can be a form of power, independent of actual formal power. In both cases actual formal power is analogous to organisational position, but Simpson *et al.* (2011*b*) did not have a measure of perceived power.

In the same year, Simpson *et al.* (2011*a*) published another article where they "*turn that work on its head*" (2011*a*, p. 172) in reference to the Simpson *et al.* (2011*b*) article. Simpson *et al.* (2011*b*) showed by way of experiments, how low-power individuals (formal low power) gained more power the more accurate their network knowledge was, but that these benefits diminished if all low-power individuals held such knowledge. The same information did not have the same strength of effect for high-power individuals. This joins Krackhardt (1990) in progressing the idea that that individuals in formal low-power positions have much to gain in spending cognitive effort in understanding their social networks.

3.5.2 Performance

With the objective of proving that individualism and structuralism should not be separated as different paradigms, Kilduff and Krackhardt set out "*investigating whether individuals' perceptions were more important than an objectively measured social structure in determining the reputations of organization member*" (1994, p. 88). What they found is that "*being perceived to have a prominent friend in an organization boosted an individual's reputation as a good performer, but that actually having such a friend (as assessed by conventional structural methods) had no effect*" (1994, p. 87). Therefore, they showed that the perception of social networks had a real substantive consequence for the performance of individuals.

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Ho and Sze-Sze (2009) also tie the consequences of cognitive network accuracy to performance, but set out from transactive memory systems theory, showing that accurate judgements of co-workers' knowledge domains relate to better performance for the group as a whole. They, however, wanted to investigate the effect on individual performance as well as the moderating role of cognitive network accuracy. They found no evidence of the moderating role of network accuracy on performance, but did reiterate the transactive memory system's findings that accurate perceptions of 'who knows what' leads to better performance, but this time for the individual.

An important point to raise here is that there should be a difference between types of performance measured. This is because the mechanisms by which performance is supposedly improved could either be human capital or social capital. Human capital relates more closely with transactive memory systems, whereas social network acuity relates to social capital. That human capital would lead to a more operational short-term performance benefit is conceivable, whereas social capital would have a more strategic non-operational benefit. Thus, if performance is measured in speed and effectiveness of performing a role or task, it would be more reliant on human capital dimensions such as transactive memory systems. If performance is measured on longer term strategic goals such as promotions or career advancement for the individual, or innovative sustainability for the organisation, social capital is more relevant. In reality, the links between capital and performance would not prove to be this clear and straightforward, but the conceptual distinction helps to organise empirical findings in this section. Especially when considering the study by Marineau (2017), who investigated the effect of network accuracy on promotion prospects. They specifically investigated how accurate perceptions of incoming trust and distrust accounts for promotions and job performance. They found strong evidence of high trust network accuracy accounting for promotions, but not for performance. In other words, high trust accuracy was important for promotion prospects regardless of performance.

Brands and Kilduff (2014) showed how respondents' cognitive network structures misrepresented women's brokerage roles when compared to the actual network, and how this reduced individual women's performance on tasks. A peculiar result from the study is when groups perceived men as occupying more brokerage roles (a gender stereotype), then the group tended to perform better. However, when the stereotype was reversed in a group (i.e. women occupy central roles), the group tended to perform worse. This finding is interesting and worthy of some elaboration. The reason the group performed better when they sub-

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scribe to the gender stereotype of male brokerage, might be because a stereotype is a form of heuristic. Most individuals are socialised to employ stereotypes as heuristics. A propagated use of such an heuristic would determine a more shared mental model of relations in the workplace. This reduces confusion and improves effectiveness of use of the social network. If they do not share the heuristic, they would have more idiosyncratic perceptions leading in less efficient interpretations of the network structure.

In a more recent study, Hahl *et al.* (2016) investigated the effect of cognitive network accuracy on the advantage of brokers. The intuitive idea is that brokers span structural holes and gain advantage, precisely because the alters are not aware of the structural hole. If the alters were aware, they would be able to dis-intermediate the broker. Notwithstanding various analytical nuances, the general findings showed asymmetry in network accuracy between brokers and alters, with brokers having more accurate network perceptions. Moreover, senders of information across a structural hole tend to have better accuracy than receivers across a structural hole—suggesting a purposeful context. The threat of dis-intermediation increased when knowledge asymmetry reduced, except when the broker is regarded as reputable. They found that brokers are better able to take advantage of their brokerage position when network perception asymmetry is higher.[18]

The finding that dis-intermediation is only a threat if the individual is not reputable, has an interesting implication: more formally acknowledged network positions are robust in the face of changing network dynamics. If one can consider a reputation as a more formalised network position, although it is not properly formal, then one finds a reason for why individuals in formal positions might have reduced motivation to explore and encode network relations in their social network. The implication is that when the asymmetry is reduced between the broker and brokered, the broker retains its reputation in brokering and might retain much of the advantages. Such an individual could be labelled as an *ambassador*, because they are formally bridging a structural hole without threat of dis-intermediation due to symmetry in network accuracy.

3.5.3 Leadership

The last article in this section is the only non-empirical article. Balkundi and Kilduff (2006) develops a theoretical model of how leader network cognition relates to their ego networks,

[18]This is an answer to the caveat given by Burt *et al.* (2013) mentioned in Section 3.2 on Page 42.

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organisational and inter-organisational networks, and how this affects leader effectiveness. There is, however, no direct empirical research to sufficiently substantiate the effect of network accuracy on leadership effectiveness. It is nevertheless a conceptually promising avenue for further research.

Subsequently, Balkundi *et al.* (2011) performed two studies, with the aim of establishing whether individuals are perceived as charismatic due to network position—which is measured in advice centrality—or do they gain the position due to their charisma. They found support in both studies for the centrality-to-charisma model. Within context, this again suggests a structuralist finding, where the network was the antecedent to the perceived leadership qualities, instead of leadership qualities that enables the person to become central.

A key concept to highlight from the above literature is SNC accuracy. The following section, therefore, investigates SNC accuracy in more detail.

3.6 Social Network Acuity

In the investigation of SNC, the idea of social network accuracy, or simply accuracy is often invoked. The idea is appealing—if people have poor recall of their social networks, and given that social relations are vital to individuals within organisations, more socially accurate individuals or groups might be special in some way. Accurate individuals should thus gain some benefit. This idea have motivated two research questions: why are some more accurate than others?; and/or what are the consequences of being accurate?

Intuitively, social acuity, being a rarity, is usually seen as a benefit. The question then becomes, how is social acuity measured? There are two general approaches already highlighted. The researcher can measure respondents' cognitions against some objective criteria including call records, email, or field observations. This is exactly what the BKS studies did. If such records aren't available, or the relation being measured does not lend itself to observation or objective recording, the researcher is left to triangulate perspectives to find some other criterion. CSS data makes it possible to triangulate some sort of criterion. However, the researcher should take care in developing the criterion. There are appeals to be more nuanced with the idea of accuracy (Koehly and Pattison, 2005; Koskinen, 2004; Ouellette, 2008).

A helpful metaphor to use in explaining the conceptual difference between accuracy and

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congruence, is to equate accuracy with target shooting and congruence to groups trying to harmonise.

When shooting at a target, there is an objectively verifiable way of determining whether the target was hit or not. It is also possible to measure the degree to which the target was reached. If any other person also shoots for the target, the observer would be able to compare the two shooters' attempts and judge which is more accurate. Accuracy is, therefore, a measure of the performance of the individual aiming parties.

In a choir, when people attempt to harmonise spontaneously, they do not have an independent target, unless they settle on a note to harmonise prior to starting. Assuming they do not have a predetermined note to harmonise on, and attempt harmonise, they will interactively find a harmony. The harmonic does not have to be the same note, especially if the note is out of the range of one of the participants. Congruence, therefore, does not assume a level of accuracy of hitting a defined target, but rather a measure of interactive competence of multiple agents. Accuracy is, therefore, a measure of the ability of a single agent and congruence measures the collaborative ability of multiple agents.

Koehly and Pattison (2005) distinguish between accuracy and consensus, where consensus is interchangeably used with congruence, or concordance. They argue that congruence measures the agreement between two or more actors, whereas accuracy measures an actor's perception against a criterion network. Such a criterion network can be an observed record, or generated from the perceptions itself. Thus, the criterion network can be defined endogenous or exogenous. Koskinen (2004, p. 3) equates accuracy to a essentialist view and congruence to a relativist perspective. The essentialist would set a single truth, from which any deviation would be a bias. The relativist view, however, problematises the idea of truth. (Batchelder, Kumbasar and Boyd, 1997) showed that, apart from direct observations or measures of behavioural records (as in the BKS studies), a conditional truth can be assumed or generated by combining the cognitions of respondents. More recently, Ouellette (2008) briefly distinguished congruence from accuracy by pointing to the study of Heald *et al.* (1998) as an example of perceptual congruence.

It is important to, therefore, be careful in determining acuity of respondents, and to be sure not to confuse acuity with the researcher's criterion. For instance, acuity rates consistently lower than 0.2 are common,[19] which suggests surveyed individuals are incapable

[19] Acuity is usually measured through correlations or distance measures that are expressed on a scale from 0 to 1, with 0 being low acuity, and 1 is perfect acuity.

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of understanding the social network surrounding them. However, the survey instruments are crude measures of complex phenomena, through which high levels of noise should be expected. Moreover, the measurements of acuity are sometimes approximate guesses in assuming what is true of social relations.

The options for actual measurement of social acuity will be expanded on in the next chapter. For now, it is prudent to settle on the idea of social acuity as a measure of individual performance in recalling either dyadic relations or structural patterns within a social network.[20] Dyadic relations are judgements on whether two individuals, John and Jill, are friends, while structural patterns are overall patterns such as; if John and Jill are friends, and Jill is also friends with Peter, John would usually be friends with Peter as well. Therefore, people might be naïve on particular dyadic relations, but still structurally competent. The next sections will expand on this.

3.6.1 Interpersonal Acuity

Previous studies measuring social acuity, including Krackhardt (1990), Casciaro (1998) and Grippa and Gloor (2009), focussed on *interpersonal* acuity. Interpersonal acuity is the measure of accuracy reliant on individual judgement of dyadic relations in the network. To measure interpersonal acuity, two matrices are compared element-wise. Consider a multidimensional array $\mathscr{R}_{kij}$, where k is the perceiver of a relation, with i the sender of the perceived relation, and j the receiver. Interpersonal acuity would, therefore, be a variant of comparing slices (k) of the array element-wise (ij) to a predefined criterion matrix ($\mathscr{R}'$). An individual's perception, $\mathscr{R}_{kij}$, is, therefore, compared to a criterion $\mathscr{R}'_{ij}$. Table 3.3 shows the four possibilities when comparing two matrices cell-wise.

TABLE 3.3: *Cell-wise comparison of slice ($\mathscr{R}_{kij}$) and criterion ($\mathscr{R}'_{ij}$) matrices.*

	$\mathscr{R}_{kij} = 1$	$\mathscr{R}_{kij} = 0$
$\mathscr{R}'_{ij} = 1$	A	B
$\mathscr{R}'_{ij} = 0$	C	D

[20] It is useful to equate structural accuracy and triadic accuracy, since triads are the smallest sub-graph that introduces structure in social relations (Simmel, 1950). However, the concept of structure is the important aspect and, for clarity, will be emphasised, instead of triadic acuity.

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A: Matching ones, meaning the ij cell in the true network is 1, and the corresponding ij cell in the criterion network is also 1. The respondent, therefore, correctly identified a relation from i to j.

B: Omission error, meaning the ij cell in the criterion network is 1, but the corresponding cell from the respondent's slice is 0. Therefore, the respondent incorrectly sees no relation from i to j.

C: Commission error, meaning the ij cell in the criterion network is 0, but the corresponding cell from the respondent's slice is 1. The respondent, therefore, incorrectly sees a relationship where there is none.

D: Matching zeros, meaning the ij cell in the true network is zero, and the corresponding ij cell from the respondent's slice is also 0. The respondent, therefore, correctly indicated no relationship from i to j.

These options measure whether the respondent is capable of correctly identifying a relation between two particular individuals (i and j). The measure is, therefore, on the dyadic level. Krackhardt (1990) considered multiple methods to create an accuracy metric, including the percentage of links correctly identified, $\frac{a}{(a+c)}$, or percentage of non-links correctly identified, $\frac{d}{(d+b)}$. They settled on a measure of S_{14} in Equation (3.6.1).

$$S_{14} = \frac{\mathrm{da} - \mathrm{bc}}{\sqrt{(\mathrm{d}+\mathrm{c})(\mathrm{b}+\mathrm{a})(\mathrm{d}+\mathrm{b})(\mathrm{c}+\mathrm{a})}} \tag{3.6.1}$$

More recently, Neal *et al.* (2016) used an adjusted version of Cohen's K to measure *target accuracy*. Target accuracy "*assesses the extent to which the observer's perceptions of classmates' relationships match the criterion, beyond what would be expected by chance*" (Neal *et al.*, 2016, p. 5). Equation (3.6.2) is the equation for their measure of target accuracy.

$$k = \frac{\Pr(\mathrm{A}) - \Pr(\mathrm{E})}{1 - \Pr(\mathrm{E})} \tag{3.6.2}$$

$$where,$$

$$\Pr(\mathrm{A}) = \mathrm{A} + \mathrm{D}$$
$$\Pr(\mathrm{E}) = ((\mathrm{A}+\mathrm{C}) * (\mathrm{A}+\mathrm{B})) + ((\mathrm{B}+\mathrm{D}) * (\mathrm{C}+\mathrm{D}))$$

Both measures convey a respondent's acuity about a relationship between any two individuals. However, it is possible to measure a respondent's acuity about the structural prop-

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erties of a network, regardless of their interpersonal acuity. The next section will expand on this idea.

3.6.2 Structural Acuity

The key proposition is that a person's structural acuity is relatively independent of interpersonal acuity. Two graphs can be structural mirrors of each other, yet be different dyadically.

To illustrate this, consider a triadic comparison in Figure 3.2. Figure 3.2a is in this case the criterion network that the other networks were compared to. Figure 3.2b is structurally equivalent to the criterion network, even though the respondent is incorrect on half of the dyadic relational judgements. The structural graph correlation confirms this ($\rho = 1$). A procedure finds the product-moment structural correlation between the adjacency matrices of graphs (see Butts and Carley, 2001, p. 30). Dyadically, the same triad has a lower correlation (S_{14} =.55 and $K = .85$). Evidently, the adjusted Cohen's K overestimates the acuity, since the empty triad in Figure 3.2d still has a high coefficient (K =.99).

Structural acuity captures the ability of people to project certain structural patterns onto the social networks they observe. Most people use schemas to encode social information (De Soto and Bosley, 1962). These schemas are useful for reducing the complexity of managing large social networks. However, some individuals might apply schemas more appropriately than others. For instance, an individual might apply the transitivity schema where the relation is not actually transitive, leading to false assumptions in perceiving the network structurally. Others might perceive higher reciprocity than normal, maybe because the cultural tendency in the particular network is for reciprocity, leading to a more correct structural encoding of the network. Larger structural patterns such as hierarchy, can also be influential in organisational social networks. People might, therefore, perceive a hierarchy where there is none, or inversely, not perceive hierarchy where there is. People use the concept of hierarchy as a guiding tool for structural considerations, particularly when the applicable culture employs an hierarchy between roles.[21] There are, therefore, structural considerations for the individual in understanding and encoding social network information that does not rely on the dyadic relation in question. Consider, for example, the effect of distance on induced triadic balance observed by Krackhardt and Kilduff (1999). People

[21]Consider corporate culture, where hierarchy, even if there is no formal form, dominates the cultural rules and norms.

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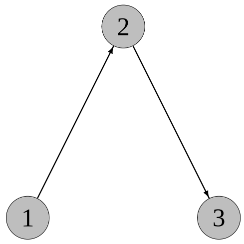
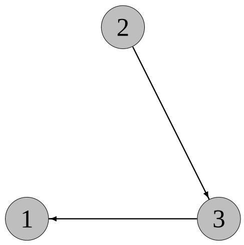
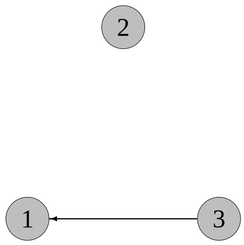


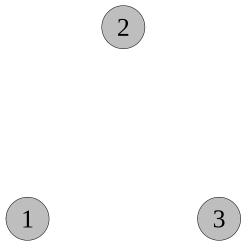
(A) *Criterion network.*



(B) *Mirrored triad.*
S_{14} = *0.55*
K = *0.85*
ρ = *1*



(C) *Half mirrored.*
S_{14} = *0.63*
K = *0.87*
ρ = *0.63*



(D) *Empty triad.*
S_{14} = *0.41*
K = *0.88*
ρ = *NA*

FIGURE 3.2: *Comparison of dyadic and structural acuity.*

employ triadic structure to infer dyadic relations, particularly when the relations are at a distance from the perceiver that obscures information about the relation.

This section has, therefore, shown that in addition to interpersonal acuity on the dyadic level, structural acuity should also be included in any investigation of a person's ability to accurately encode and recall social relations. This is because, it is reasonable to expect that a particular individual is incorrect on a particular dyadic relation, but is well attuned to the structural patterns in a social network. They are, therefore, better able to identify local and global clustering coefficient, as well as accurately encode social hierarchies. By only measuring dyadic acuity, the researcher, therefore, risks losing a lot of SNC information.

Observing that certain individuals are more accurate, prompts the researcher to ask why this might be. Few have explicitly investigated SNC accuracy, and from those who have, the predominant assumption generally leads to ascribing acuity to favourable network factors, in particular the social network position, such as centrality. It is reasonable to, therefore, cast the net wider in the search for antecedents to an individual's accurate network percep-

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tion, such as a focus on personality or particular organisational and social contexts. The scope will, however, stay on network position. Thus, the next section investigates the relation between SNC acuity and social network position.

3.7 Acuity and position

Previous authors have linked social position to acuity by showing that more central people have more accurate cognitive representations of their social networks (Casciaro *et al.*, 1999; Grippa and Gloor, 2009; Krackhardt, 1990). Others have shown that social position at least plays a role in similar network cognitions, regardless of acuity (Krackhardt and Kilduff, 2002; Romney and Faust, 1982). This section will investigate the theoretical argument driving this relation between social acuity and position.

Social position can be defined through either formal or informal observations, resulting in formal or informal positions. A formal position is usually operationalised as the organisational hierarchy, or organisational group membership where there is a relation between the groups. The position is made formal through the explicit and consistent organisation wide acknowledgement of the position and the inherited implications for individuals in the position. All individuals, in the organisation at least, will be able to interpret relational deductions such as superior and sub-ordinate roles (hierarchy), or be able to know that a director is above a manager (group membership).

An informal social position is the position an individual holds in the informal social network, based in relations such as trust or friendship. These positions are not formally defined, and are ephemeral in their formation and interpretation. There are multiple possible positions in a social network, but some are often regarded more important than others. Centrality is one of the more popular measures of informal network position. The importance of a central node is an intuitive idea, and many have shown that this is indeed the case (Borgatti, 2005; Borgatti and Everett, 2006). Four popular measures of centrality are degree, betweenness, closeness, and eigenvector.[22]

Casciaro (1998) hypothesised that certain informal social positions, such as centrality, would lead to SNC acuity. The argument was made through three *processes* borrowed from Pattison (1994).

[22]The exposition of each centrality measure is captured later in Section 4.3, but it is important to name them here.

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The *first* argument is the most intuitive; "*a person's position in the social structure may be related to cognition because it contributes to determining what information a person* [is] *exposed to*" (Casciaro, 1998, p. 334).[23] Assuming the flow model of social networks would suggest that people with higher centrality will have more access (degree) or novel (betweenness) information about interactions between people. Pattison (1994) labels this as "*information bias*", and argues that individuals in the most central network positions should have the most knowledge of social ties. Since the position dictates the information available to a person i.e., to what they are exposed, it composes their individual cognitions of the network.

The *second* argument is related to interaction history that was later empirically tested by Janicik and Larrick (2005). The argument is based on the proposition that exposure to certain patterns of interaction would dictate cognition, since repeated exposure to certain patterns of social interaction should lead to recognising these patterns more easily. Janicik and Larrick (2005) show how previous exposure to structural holes predicts the ease by which individuals learn such patterns in a new environment.

The *third* argument relies on consistency theories such as Heider's structural balance theory. The proposition is that an individual's cognition is influenced through their immediate social position relative to others. For instance, in balance theory, if *A* likes *B*, and *B* likes *C*, then *A* would tend to exhibit the same affective relation i.e., *liking*, with *C*. Therefore, *A*'s perception of *C* is influenced by the perception of *B*'s relation with *C*. An example of this effect in action is the study of Kilduff and Krackhardt (1994), who investigated the basking-in-reflected-glory effect. The effect is not limited to immediate proximity in a network, but can be extended to similarity such as regular equivalence (Pattison, 1993).

These arguments fit well with the *network creates the people* assumptions of classic structuralist research, since the often cited tenet opens Pattison's argument: "*the opportunities for and circumstances of social interaction are not random, but instead they are distributed according to the patterns defined by the social structure*".

The argument of Pattison (1994) focuses on similarity in position leading to similarity in cognition that resembles the work of Krackhardt and Kilduff (2002) on cultural agreement. This is also the basis for Carley's constructural theory. The study by Casciaro (1998), however, quietly diverts to a more specific hypothesis, linking specific social position (centrality) to specific cognition (accuracy).

[23] Square brackets are not original.

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To move forward from the above argument, it is pertinent to first expand the notion of social position, as used by the authors above, to include formal organisational positions.

Casciaro (1998) uses an organisational hierarchy as the measure of formal position. Since formal position is just a formalised form of social structure, some advantage afforded to informal positions is expected to extend, or translate, to the formal variants. Moreover, these positions are indeed formalised advantageous positions, of which all members of the organisation are aware. Therefore, if the three arguments above are also applied to formal positions, the same should hold: formal position positively influences social acuity.

Related to the first argument, *information bias*, people in formal positions are privy to information that their subordinates are not, and should, therefore, have an advantage in perceiving social relations. Following the second argument of *interaction history*, people higher up in the hierarchical network would have more experience with structural holes, or mediating positions, than those at the lower end of the hierarchy. They should, therefore, be better equipped to observe such relational patterns. Lastly, formal positions are well-defined positions, which translates across contexts, offering a consistent pattern of interactions which should parallel the *consistency argument*.

If informal social positions, usually centrality, can be extended to formal positions such as hierarchical positions, it is a basic inference to also extend the advantages—like being more accurate about the social environment. However, when considering acuity, Krackhardt (1990) could not find evidence of a relation, and Casciaro (1998) found a strong negative relation between hierarchical position and social acuity.

The reason posited for these findings is that people higher in the hierarchy do not need to invest their cognitive energies in monitoring social interactions, since they are already afforded the advantages of a social position. This reason is easy to agree with, however, if it is extended back to the underlying processes it becomes problematic. This is because the underlying processes proposed by Pattison (1993), and built on by Casciaro (1998), does not require such a motivation.

If social acuity is due to access to information afforded to beneficial positions, either formal or informal, then those occupying the positions can be passive occupants and still receive the benefit, since their peers who do not occupy such a position will not have access, even if sought. Then, surely, if an individual occupies a formal variant it is not concordant to argue that they actively ignore the information provided by the position.

Therefore, the observed effect—that acuity does not extend to formal positions—cannot

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be explained by ascribing agency to the occupant of the position, while ignoring agency in the original theorisation of the role of structure. It is, additionally, contrary to the call set out by Kilduff and Krackhardt (1994), to incorporate the individual back into SNA by acknowledging purposeful action by constituents of a network, and not to rely exclusively on the structuralist trap of seeing nodes as mere passengers of social networks.

In affording agency to individuals, it might be better to theorise that formal hierarchy removes the motivation to be socially accurate that leads to lower levels of acuity the higher up in the hierarchy a person is. Therefore, the potential benefit motivates social acuity for those that make the effort, or have a predisposition. The motivation is mostly relieved when a position is secured through a formal position. Recall the finding that individuals with formal power do not gain much benefit through being socially accurate, as those with less power. It is, therefore, a reasonable strategy to relax the motivation to be socially aware. The assumption of direction of causality should, therefore, be reversed: acuity leads to informal network position. In the next section, the case is made for reversing the hypothesised effect between acuity and position, and will outline how this could be tested.

3.7.1 A Case For The Reverse: 3 Hypotheses

The first question could then be; does social position cause acuity or does acuity cause social position? However, it would be naïve to dictate the direction of causality exclusively in one direction. Tasselli *et al.* (2015) appealed for a more recursive view of social networks. Borgatti and Halgin (2011*b*) argue that, whether someone reaches a certain network position on purpose or accident, the position is still related to certain advantageous outcomes. This insight highlights the motivation for a two-way consideration of social network acuity. The narrative prior to this study has, however, considered the direction of causality, at least theoretically, only in one way: network position dictates cognition. A case is, therefore, proposed for the reverse to consider that social acuity results in network position.

The central theory presented by Casciaro *et al.* (1999) for why social network position leads to accurate SNC is that their positions provide access to the information about the structure. They then proceed to explain why this is not the case for formal positions. The forwarded explanation is that there is no motivation for someone in a formal position to use the information. Their explanation, therefore, involves two mechanisms, where the one is embedded in structuralist thought, and the other includes agency. It might be better to

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propose a single mechanism that would explain both observations. Such a mechanism would posit the argument that SNC acuity leads to position, because individuals who are more accurate, know about, and can take advantage of available positions. The approach presents a single mechanism focusing on the agency of the individual and the effect of cognition on social position. This is contrary to Casciaro (1998)'s argument, through Pattison (1994), portraying individuals as passive passengers within network positions.

Being central in a network has intuitive appeal to social agents, even if they are not aware of network positions such as centrality. People do not set out to become 'more central', but they do, however, vie for popularity, or intend to *keep their enemies closer*, or consider *a friend of a friend is a friend*, and many do actively *network*. The benefits of these efforts are merely formally represented by measures such as degree or betweenness centrality. People do, therefore, actively attempt to control and change their social position through various strategies. The particulars of those strategies are not of importance at this point, since it can be abstractly treated as motivational actions by individuals with the objective of more advantageous positions.

Individuals spend effort to understand and navigate social networks, thus, the individual who is accurate about the network structure wastes their acuity if they do not use that information to position themselves into a more favourable network position. Moreover, a person in a favourable network position will use the position without having to resort to network acuity. This suggests why people that are higher in a hierarchy are less accurate, since their position formally offers them the advantages related to it. Individuals in an informal advantageous position would however, have to keep their motivation for social network accuracy, since the position is more ephemeral, and as Hahl *et al.* (2016) has shown, a predictor of brokerage positions is network acuity differentials within the network. These individuals, therefore, have more motivation to stay socially aware than those occupying formal positions.

The argument for the reverse of direction of causality can be derived through the existing literature, but it would be better to be able to formally define hypotheses to test this theory. A key set of structural hypotheses are, therefore, proposed that will be tested empirically. The hypotheses are discussed below.

The first hypothesis is that formal position has no significant relation with social acuity. The alternatives are, therefore, that there is a significant positive or negative relation between the two variables. Accordingly,

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Hypothesis 1a (H1a) *There is no significant relation between formal position and social acuity.*

Hypothesis 1b (H1b) *There is a significant negative relation between formal position and social acuity.*

Hypothesis 1c (H1c) *There is a significant positive relation between formal position and social acuity.*

H1a will confirm the findings of Krackhardt (1990), and H1b will confirm the finding of Casciaro (1998). H1c will be a new finding that contradicts all prior research.

If H1a or H1b is confirmed, the proposed argument will hold. This is because a positive relation between formal position and social acuity would validate the opposite argument that social position (whether formal or informal) would lead to social acuity. As long as there is no relation, or positive relation, the argument that acuity leads to informal social position is still feasible.

The next hypothesis is that formal social position will relate with informal social position on certain relational measures, such as advice. This is to validate the extension of informal position to formal position. If formal position does correlate with certain informal relational networks, the argument for *similar benefits* is feasible.[24] The interaction with particular relational dimensions will mostly rely on organisational culture. For instance, if there is a strong hierarchical tradition, people will not be friends, or at least report such, with superiors, or people outside their membership group, since this might be inappropriate. The hypotheses are therefore:

Hypothesis 2a (H2a) *There is no significant relation between formal and informal social positions.*

Hypothesis 2b (H2b) *There is a significant positive relation between formal and informal social positions.*

Hypothesis 2c (H2c) *There is a significant negative relation between formal and informal social positions.*

If H2a is confirmed, the extension of network benefits from informal to formal structures does not hold, however, if any of H2b or H2c are confirmed, the extension holds. This

[24] Recall that if there is a relation between informal and formal social positions, the observed benefits of informal social position, such as SNC acuity, should be observed for formal positions.

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is because if there is a positive interaction on relations, such as advice, then higher formal positions are essentially a formalised variant of the informal structure, and all benefit should apply. If there is a negative interaction between formal and informal social positions, it means that informal social positions are avoiding redundancy with formal social positions. The argument is nevertheless more convincing if H2b is confirmed.

The third hypothesis highlights the final necessary interaction; acuity leads to informal social position. Previous research have already confirmed a relation, however, through non-parametric regression analysis, the reversed direction of causality should be tested (Casciaro, 1998; Grippa and Gloor, 2009; Krackhardt, 1990). The hypotheses are as follows:

Hypothesis 3a (H3a) *There is no significant relation between social acuity and social position.*

Hypothesis 3b (H3b) *There is a significant positive relation between social acuity and social position.*

Hypothesis 3c (H3c) *There is a significant negative relation between social acuity and social position.*

Either H3a or H3c would invalidate the proposed argument, and partly contradict all previous research.[25] H3b would validate the argument, since it repeats the previous observations by research linking a relation between informal social positions and social network acuity, and includes the direction of causality between the two variables.

3.8 Conclusion

This chapter opened with a description of the importance of social cognition for organisational life, while juxtaposing it with the findings that individuals are surprisingly inaccurate about social relations when compared to objective criteria. The chapter then proceeded to highlight the attempt of SNCA to investigate and understand how people perceive social networks. Some researchers investigated what the causes are for the distortions in individual perceptions of their social networks by investigating the schema people employ in simplifying such a complex network of relations. Others were more interested in investigating what the consequences are of such distortions in perception. The argument would be,

[25] *Partly*, because the assumption of direction in the regressions will be that causality is in the opposite direction of previous studies.

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and the themes attest to it, that accurate perceptions lead to advantages for those that are either better equipped or make a greater effort in monitoring social relations. These themes are power and leadership, where social acuity is thought to lead to individual advantages to the enterprising and socially aware.

The chapter proceeded to focus on a particular assumption in the literature, that social position explains why people are more accurate than others. This assumption is problematised. A key step was to establish an extension of informal position to formal positions. This would establish a case: the advantages available to informal social positions—such as becoming socially accurate—should, to some extent, be extended to formal positions. Prior research on the interaction between three key variables—informal social position, formal position and SNC acuity—are used to outline the argument for the reversal of the direction of interaction, suggesting that social network acuity leads to social position. This is built on a mechanism that ascribes more agency to individuals in the network structure, but still acknowledging the tenet that the structure offers benefits to those in favourable positions. Many individuals instinctively want to position themselves into a more beneficial social standing, and to do so, they would have to find vacant positions, or disconnected clusters, or more friends, to be able to receive the benefits of the network.

Finally, three hypotheses are outlined to be tested empirically. It is the objective of the next chapter to expand on how the hypotheses would be tested by navigating the unique requirements of CSS datasets, and formulating a specific methodological procedure to apply to the three datasets to support the argument developed here.

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PART II

METHODOLOGY & ANALYSIS

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CHAPTER 4

METHODOLOGY

The previous chapter explored the concept of social network cognition (SNC) through the field of social network cognition analysis (SNCA). In particular, SNC acuity is highlighted as a particular interest. A key assumption, placing network position as the cause of accurate network perceptions, was critically examined. This led to a proposal for investigating the reverse interaction: being accurate about social relations in an organisation leads to beneficial positions within the social structure. To investigate this assertion, three hypotheses were put forward to be tested.

The current chapter has three key contributions in the light of the above. *First*, to empirically test the hypotheses, data needs to be gathered. The data gathering procedure is outlined in Section 4.1. *Second*, these datasets produce a three-dimensional data structure, and network measures such as centrality, require a two-dimensional structure. The datasets, therefore, need to be processed. The procedure is explained in Section 4.2. *Lastly*, Section 4.3 highlights the social network measures of interest. Another methodological consideration, the measure of SNC accuracy, was already introduced in Section 3.6 of Chapter 3 and will, therefore, not be expanded on here.

4.1 Data Collection

Recall that there are three variables of interest: individual informal social position; individual formal position; and individual SNC acuity. To empirically test the hypotheses requires all three variables observed for a group of individuals. The cognitive social structure (CSS) roster method, as proposed by Krackhardt (1987*a*), provides two of the three variables: informal social position and SNC accuracy. For the third variable, an organisational hierarchy or grouping would be appropriate to deduce the formal position of each individual.

It would be beneficial to utilise more than one dataset for two reasons. *First*, the CSS roster method can practically only be applied to a small network. To empirically test the hypotheses, more observations would be beneficial in improving the confidence of the empirical tests. *Second*, a survey of different organisational contexts would contribute to im-

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TABLE 4.1: *The three datasets.*

Attribute	HighTech	SilSys	Pharma
Size	21	36	19
Missing Responses	0	0	2
Number of relations	2	2	5
Relations	Friendship Advice	Friendship Advice	Friendship Advice Trust Persuasiveness Knowledge
Data Gathering Method	CSS Paper Survey	CSS Paper Survey	CSS Electronic Survey
Question Phrasing	Direct Supposition	Direct Supposition	Indirect Hypothetical
Organisational Context	Small technology manufacturing firm	Information-System Entrepreneurial firm	Large pharmaceutical services firm
Organisational Context	Management	Whole Site	Whole Department
Hierarchical Levels	3	3	5
Organisational Size	Single site	Single Site	Single Site
Location	USA	USA	RSA
Collection Year	1987	1992	2017

proving the external validity of the methodology, while also offering more control variables such as network size and number of hierarchical levels that only differ between sites.

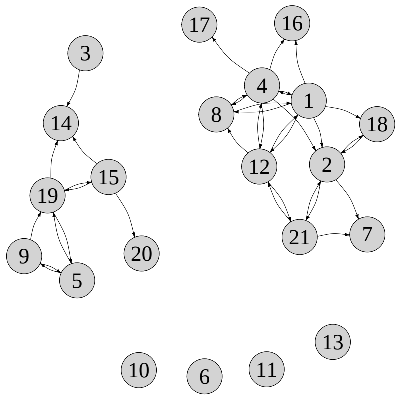
To summarise, the needs for the data are as follows:

- It should utilise a CSS roster method to gather full cognitive social network data;
- It must be done in an organisational context;
- It should include two relational dimensions: friendship and advice;
- It should have two or more formal hierarchical levels.

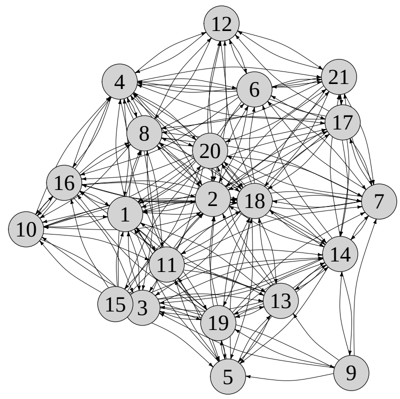
There are two publicly available datasets that satisfy the above criteria. The first is known as the *High Tech Managers* (HighTech) dataset produced through the study by Krackhardt (1987*a*). The second is the *Silicon Systems* dataset gathered in 1992, again by Krackhardt. A third unpublished dataset, Pharma, also satisfies the above criteria. More details of each dataset are provided in the following sections. Additionally, a summary table for each is provided in Table 4.1

4.1.1 High Tech Managers

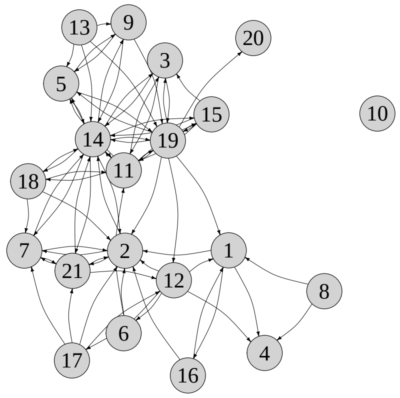
The HighTech data, gathered by Krackhardt (1987*a*) surveyed 21 managers at a small technology manufacturing firm consisting of 100 employees. The study asked of respondents to provide their judgement on two social relations: friendship and advice. To elicit the advice relation, respondents were presented with a paper-based survey consisting of direct supposition questions such as *"who would Steve Boise go to for help or advice at work?"*, and *"who would Steve Boise consider a friend?"* (Krackhardt, 1987*a*, p. 118). In keeping with the CSS methodology, this question was then repeated for the other 20 managers. Figure 4.1 below offers the reader a view of the social perceptions of two individuals (4 and 19).



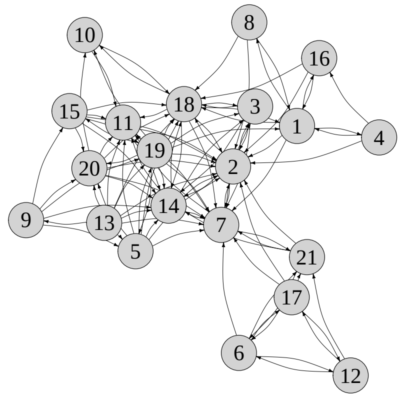
(A) *Respondent 4 perception of freindships.*



(B) *Respondent 4 perception of advice.*



(C) *Respondent 19 perception of freindships.*



(D) *Respondent 19 perception of advice.*

FIGURE 4.1: *High Tech Managers sample of cognitive perceptions of social relations by respondents 4 and 19.*

4.1.2 Silicon Systems

The SilSys dataset, gathered by Krackhardt (1992), surveyed the largest network with 36 respondents. As with the HighTech dataset, they asked respondents to provide judgement

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on two relations: advice and friendship.

SilSys was a small entrepreneurial firm located in the United States. Their key business was selling, installing and maintaining information systems for clients. The study surveyed all employees at the organisation, since they are on one site, and there is a reasonable expectation that everyone knows everyone. They, therefore, captured three hierarchical levels. The top-level is the three equal partner top managers. The firm witnessed staff growth from three to 36 people in the 15 years of its existence, with the bulk of the growth happening in the five years prior to the study. They used the same data gathering methodology as with the HighTech dataset.

Respondents 13, 24, and 35 had a partial response. Figure 4.2 is again a sample from this dataset highlighting the two relations for two individuals (4 and 12).

4.1.3 Pharma

The Pharma data was gathered at the human resources department of a large pharmaceutical organisation in South Africa. The department consists of 19 members, with five hierarchical levels. Two members, 5 and 15, did not answer the survey.

As opposed to the previous two datasets, the respondents were prompted for five relational dimensions instead of only two.[1] This was feasible since the group is small enough to not be an extra burden, and the electronic questionnaire instrument could make it easier to answer more questions. The five dimensions were; friendship, advice, trust, persuasiveness, and knowledge. The phrasing of the questions were different compared to SilSys and HighTech. Accounting for the sensitivity and burden of the questions, such as trust relations, the questions were phrased as indirect hypotheticals. Counter to the indications of De Lange, Agneessens and Waege (2004), hypothetical questions were preferred since the recall objectivity of the responses are less important. With the hypothetical phrasing, respondents could answer about relational dimensions in an ideal context, instead of relying on recall. Since respondents are providing judgements on relations between people not involving themselves, and they might not be able to recall evidence from memory such as prompted by questions similar to whether i considers j a friend. However, they can offer an honest opinion about whether i might invite j to a gathering celebrating a personal milestone.

[1]An example of the questions is available in Appendix B.

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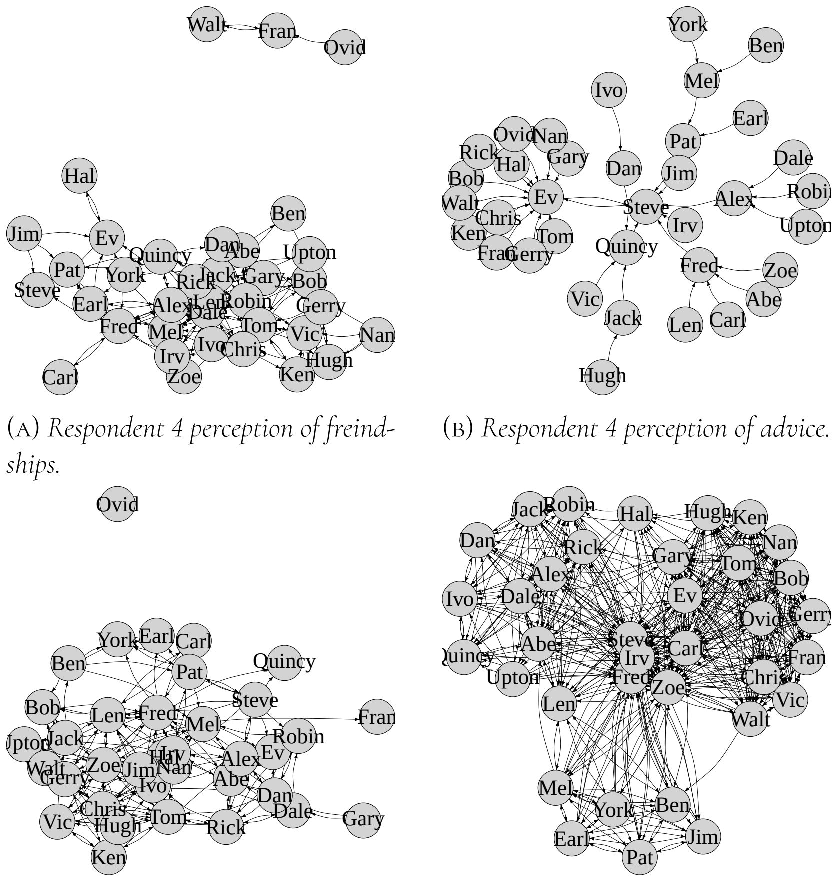

(A) *Respondent 4 perception of freindships.*

(B) *Respondent 4 perception of advice.*

(C) *Respondent 12 perception of freindships.*

(D) *Respondent 12 perception of advice.*

FIGURE 4.2: *Silicon Systems sample of cognitive perceptions of social relations by respondents 4 and 12. The readibility of particular relations decreases with larger and denser graphs, as such the case with D. However, it is the global structure and pattern that is of interest.*

Figure 4.3 highlights a sample of two respondents (13 and 17) on only the advice and friendship relations, since these are the only relational dimensions of interest.

Since the data produces a full CSS dataset, the next section discusses the available methods of reducing the datasets to a format amenable for social network metrics.

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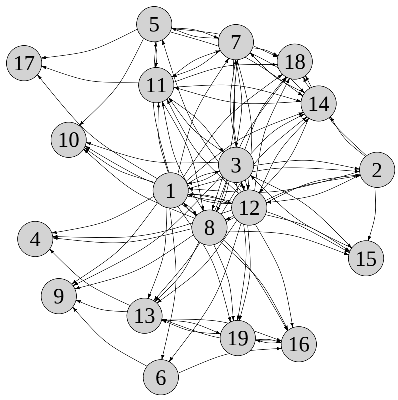
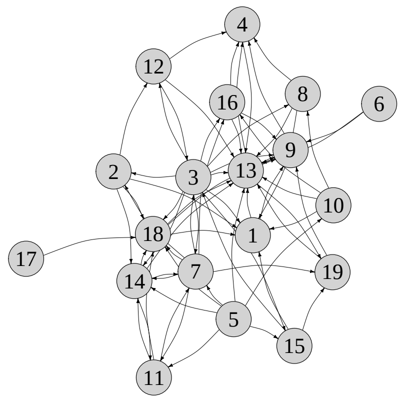
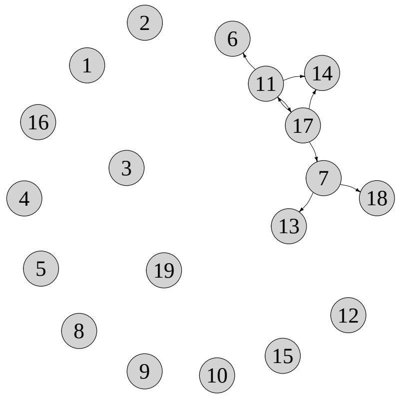


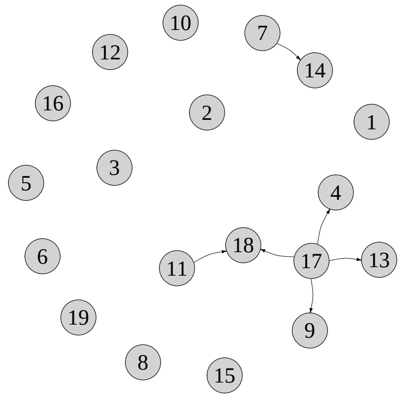
(A) *Respondent 13 perception of freind-ships.*



(B) *Respondent 13 perception of advice.*



(C) *Respondent 7 perception of freind-ships.*



(D) *Respondent 17 perception of ad-vice.*

FIGURE 4.3: *Pharma sample of cognitive perceptions of social relations by respondents 13 and 17.*

4.2 Creating Reduced Networks

As highlighted in Section 3.3.1, CSS data is more extensive than standard network datasets. Since it is more elaborate, it offers the researcher scope for more questions. For instance, a routine first question in SNA is: '*who is most central?*'. In normal SNA datasets, one would simply query the network for a centrality measure. However, with CSS data the answer is: '*according to whom?*'

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4.2.1 Cognitive Social Structure Data

CSS data generates a three-dimensional network structure ($\mathscr{R}_{k,i,j}$) where $\mathscr{R}$ is the relation from i to j as perceived by k. To compute network metrics, the dataset needs to be reduced to a two-dimensional format. The simplest way would be to hold k constant, or in other words, to only extract the perception of a single respondent. As an example, k can be set to respondent 3, thus $\mathscr{R}_{3,i,j}$ would produce the socio-matrix in Table 4.2, with the corresponding sociogram in Figure 4.4.

TABLE 4.2: *Advice socio-matrix of respondent 3 from the HighTech dataset.*

$\mathscr{R}_{3,i,j}$	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21
1	0	1	1	0	1	0	0	0	0	0	1	0	1	1	0	0	0	1	1	0	0
2	1	0	1	1	1	1	1	1	0	0	1	1	1	1	0	0	1	1	1	0	1
3	1	1	0	1	0	1	1	1	1	1	1	1	0	1	0	0	1	1	0	1	1
4	0	1	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0
5	1	1	0	0	0	0	1	0	0	0	1	0	0	1	0	0	1	1	0	0	0
6	0	1	0	1	0	0	1	0	0	0	0	1	0	1	0	0	1	0	0	1	1
7	0	1	1	1	0	1	0	1	0	0	1	0	0	1	0	0	1	1	0	1	1
8	0	1	1	0	0	0	0	0	0	1	1	0	0	1	0	0	0	1	0	0	1
9	0	0	1	0	1	0	0	0	0	0	0	0	1	1	0	0	0	0	1	0	0
10	0	1	1	0	1	0	1	1	0	0	1	0	1	1	0	1	0	1	1	1	0
11	1	1	1	0	1	0	1	1	0	1	0	0	1	1	0	0	0	1	1	0	0
12	0	1	0	1	0	1	1	1	0	0	0	0	0	1	0	0	0	1	0	0	1
13	1	1	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	1	0	0	0
14	0	1	1	0	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1
15	0	1	0	0	0	0	1	0	0	0	1	0	0	1	0	0	0	1	0	0	0
16	0	0	0	0	0	0	0	0	0	1	1	0	0	1	0	0	0	1	0	0	0
17	0	1	1	0	1	1	1	1	0	0	0	1	1	1	0	0	0	1	1	0	1
18	0	1	1	0	1	0	1	1	0	1	1	0	1	1	0	1	0	0	1	0	0
19	1	1	0	0	0	0	1	1	0	1	1	0	0	1	0	0	1	1	0	1	0
20	0	1	1	0	1	1	0	0	0	0	0	0	1	1	0	0	0	0	1	0	0
21	0	1	1	1	0	1	1	1	0	0	0	1	0	1	0	0	1	0	0	0	0

The primary focus of this section is to investigate the various methods of reducing multiple networks into some representative network. The concern is not whether the representation is indicative of objective reality. Furthermore, the comparison between the product of these reductions and the individual slices is reserved for the next section.

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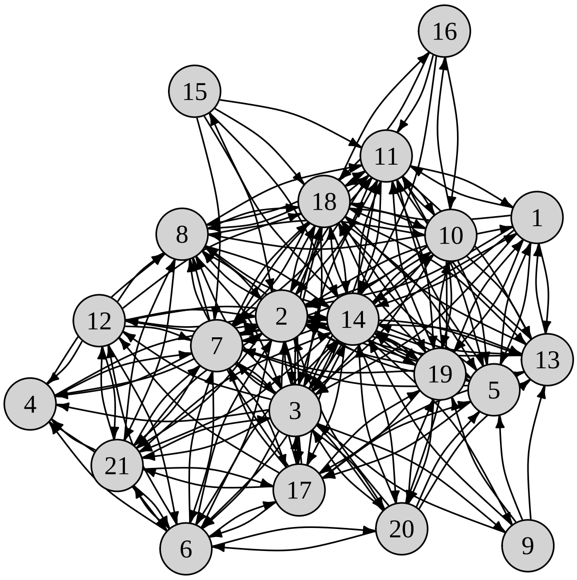

FIGURE 4.4: *Advice sociogram of respondent 3 from HighTech dataset.*

4.2.2 Creating Reduced Networks

There are three motivations for reducing a collection of slices into a single network. The *first* would be to create a two-dimensional network to analyse descriptively, while avoiding the issue of only using a slice—in other words, the view of a single respondent. The *second* motivation is to generate a true network to which the slices can be compared. The resulting reduced network is thus a means to an end. The *third* motivation is interested in reducing multiple graphs into one, but the primary objective is to deal with missing or noisy data, with the added benefit of building a model, allowing for sampling procedures. Only the first two motivations are of interest here.

Krackhardt (1987*a*) developed three broad methods of composing a network from multiple sources; *cognitive slice*, *locally aggregated structure* and *consensus*. Other methods can be grouped into *expert* or *cultural* models of network reduction that is mostly from the work of Romney, Weller and Batchelder (1986) and Batchelder *et al.* (1997) on cultural consensus research. Another grouping, which is aligned with the third motivation above, is from Siciliano, Yenigün and Ertan (2012) and Yenigün, Ertan and Siciliano (2017) that can be grouped as *sample* methods. Each grouping will be discussed below as with a brief description of each method.

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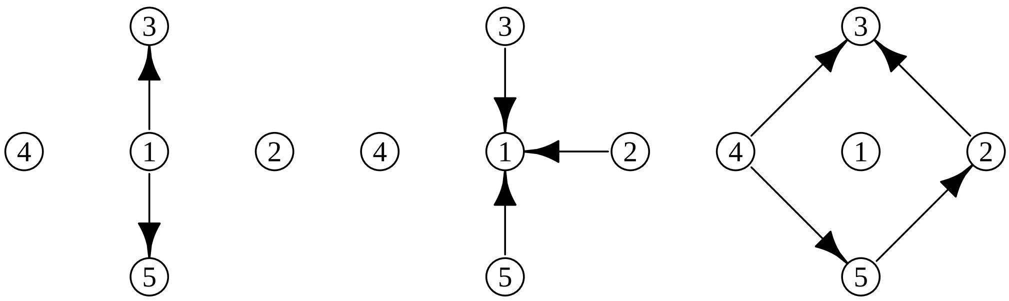
4.2.2.1 Cognitive Slices

A cognitive slice is a representation of one respondent's perception of a social network regarding a certain relational dimension, such as friendship or advice.

Asking respondents to not only offer their own ego network, but to provide judgement of all other alters' ego networks, produces a cognitive slice. One question, therefore, contains three implicit questions: (1) who do you talk to? (2) who talks to you? (3) who talks to whom, other than you?

These implicit questions are shown graphically Figure 4.5. The corresponding data matrices for Figure 4.5 are shown in Tables 4.3a, 4.3b and 4.3c.



(A) *Who do you talk to?* (B) *Who talks to you?* (C) *Who talks to whom?*

FIGURE 4.5: *Three implicit questions of CSS: networks.*

TABLE 4.3: *Three implicit questions of CSS: adjacency matrices.*

$$
\begin{array}{c}
\mathscr{R}_{ijk} \\ i_1 \\ i_2 \\ i_3 \\ i_4 \\ i_5
\end{array}
\begin{array}{c}
\begin{array}{ccccc} j_1 & j_2 & j_3 & j_4 & j_5 \end{array} \\
\begin{bmatrix}
 & 0 & 1 & 0 & 1 \\
\cdot & & \cdot & \cdot & \cdot \\
\cdot & \cdot & & \cdot & \cdot \\
\cdot & \cdot & \cdot & & \cdot \\
\cdot & \cdot & \cdot & \cdot &
\end{bmatrix}
\end{array}
\cdots
\begin{array}{c}
\begin{array}{ccccc} j_1 & j_2 & j_3 & j_4 & j_5 \end{array} \\
\begin{bmatrix}
 & \cdot & \cdot & \cdot & \cdot \\
1 & & \cdot & \cdot & \cdot \\
1 & \cdot & & \cdot & \cdot \\
0 & \cdot & \cdot & & \cdot \\
1 & \cdot & \cdot & \cdot &
\end{bmatrix}
\end{array}
\cdots
\begin{array}{c}
\begin{array}{ccccc} j_1 & j_2 & j_3 & j_4 & j_5 \end{array} \\
\begin{bmatrix}
 & \cdot & \cdot & \cdot & \cdot \\
\cdot & & 1 & 0 & 0 \\
\cdot & 0 & & 0 & 0 \\
\cdot & 0 & 1 & & 1 \\
\cdot & 1 & 0 & 0 &
\end{bmatrix}
\end{array}
$$

(A) *Who do you talk to?* (B) *Who talks to you?* (C) *Who talks to whom?*

The data from Table 4.3 is recorded as a single matrix, such as in Table 4.4. The ego network, captured with the first two implicit questions, is combined with the whole net-

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work data captured through the third implicit question. This dataset is called a *cognitive slice* (Krackhardt, 1987*a*). (Siciliano *et al.*, 2012, p. 586) adopts an intuitive way of dealing with the difference by labelling the result of the first two questions as *knowledge* and the third implicit question as *perception*. Strictly speaking, all the implicit questions provide perceptions and not knowledge. This confusion leads to an indictment of the BKS critique.

TABLE 4.4: *Individual CSS: slice.*

$$
\begin{array}{c c}
\mathscr{R}_{ijk} & \begin{array}{ccccc} j_1 & j_2 & j_3 & j_4 & j_5 \end{array} \\
\begin{array}{c} i_1 \\ i_2 \\ i_3 \\ i_4 \\ i_5 \end{array} &
\begin{bmatrix}
 & 0 & 1 & 0 & 1 \\
1 & & 1 & 0 & 0 \\
1 & 0 & & 0 & 0 \\
0 & 0 & 1 & & 1 \\
1 & 1 & 0 & 0 &
\end{bmatrix}
\end{array}
$$

A cognitive slice is, therefore, captured from one respondent. All other respondents in the network contribute their cognitive slices, thus creating a multidimensional array of $N \times N \times N$.

To express this process more formally, $\mathscr{R}_{ijk}$ is elicited, where k is the perceiver of relations between a sender i and receiver j. Here, $\mathscr{R}_{ijk} = 1$ means that k perceives that a relation exists from an actor i to j, and $\mathscr{R}_{ijk} = 0$ means that k perceives the relation not to exist.

The drawback to this method is that it is merely slicing a part of the dataset that results in an individual perception. This is not useful if the objective is to distil the network into a criterion, unless the criterion should be a particular respondent's perspective.

Instead of relying on one particular perspective, all perspectives can be combined to produce a single two-dimensional matrix. There are three general approaches to achieve this. *First*, the slices can be combined by using a local rule defining whether $i \rightarrow j$ = 1. The result is called a locally aggregated structure (LAS). *Second*, some form of average can be taken from the slices that would result in a consensus. *Finally*, experts can be selected, or weighted, to define a criterion. This could be labelled as expert methods. The next sections explore each in turn.

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TABLE 4.5: *LAS methods.*

Method	Description	Substantive Rationale
RLAS	Perspective of i dominates	Who do you like?
CLAS	Perspective of j dominates	Who offends you?
ILAS	Both i *and* j must agree of $i \to j = 1$	Who is your friend?
ULAS	Either i *or* j must perceive $i \to j = 1$	Who goes to whom for advice?

4.2.2.2 Locally Aggregated Structures

LAS methods are considered locally aggregated since the resulting relation of $i \to j$ relies on the local members, namely i and j (Krackhardt, 1987*a*). The methods are: *row-dominated* LAS (RLAS), *column-dominated* LAS (CLAS), *intersection* LAS (ILAS) and *union* LAS (ULAS). Table 4.5 offers a summary of the methods.

The resulting sociograms from the four methods are shown in Figure 4.6. The methods were applied to the same dataset (Pharma) on the friendship relation. It is observed in Figure 4.6 that the resulting networks differ drastically, depending on the reduction method.

4.2.2.2.1 RLAS RLAS assumes that k determines the veracity of their outgoing ties. Thus, in constructing the RLAS network, all rows are preserved where $k = i$. This produces a single square matrix consisting of outgoing perceptions from each respondent as the respondents themselves perceive it. Substantive contexts where this method is applicable, are where the sender of a relation can be regarded as the authority of whether the relation exists, irrespective of the receiver. An example would, therefore, be affective relations such as liking another person. An individual cannot control who likes them, but they can control who they like. Uncovering *who likes whom* would, therefore, rely on the sender of the relation to determine the veracity, regardless of the receiver.

4.2.2.2.2 CLAS Contrary to RLAS, CLAS assumes that k determines the veracity of their incoming ties. Therefore, to construct the CLAS network, all columns are preserved where $k = j$ that produces a single square matrix consisting of the perception of incoming relations according to the respondents themselves. Substantively, this method is applicable in a case where the receiver of a tie is the authority of whether the relation exists. For instance, asking *who offends whom* will not rely on the *sender* of offence to indicate whether

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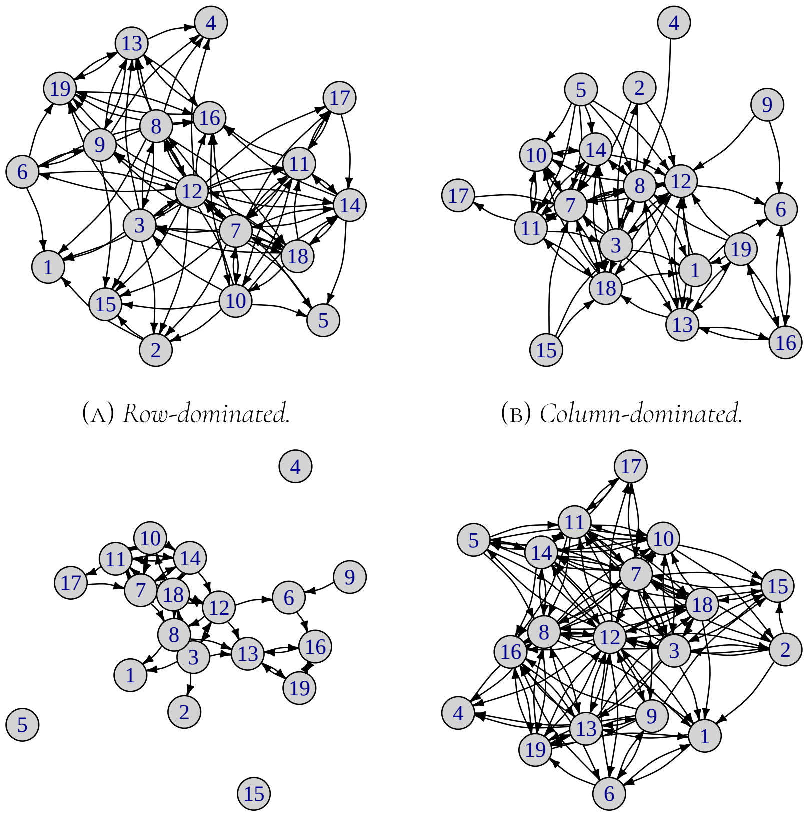

(A) *Row-dominated.* (B) *Column-dominated.*

(C) *Intersection rule.* (D) *Union rule.*

FIGURE 4.6: *Reductions of friendship relation from the Pharma datasets using the LAS methods.*

there is an offensive link, but rather the person taking offence, independent of whether the sender intentionally offended the other person..

4.2.2.2.3 ILAS ILAS is the strictest LAS method. ILAS is calculated by deriving the intersection between both i and j, thus $\mathscr{R}'_{i,j} = \mathscr{R}_{i,i,j} \cap \mathscr{R}_{j,i,j}$ (Krackhardt, 1987*a*). Substantively, this would be an applicable method for when both the receiving and sending party are required to confirm a relation, such as with friendships. One might consider another a friend, but if it is not confirmed, the relation does not independently exist beyond the perception of the sender. Likewise, if the receiver considers another as being friends with him/herself, but it is not confirmed by the sender, the relation is not objectively verified beyond the reciever's perception. Thus, an individual might think he is popular, thus indicating many friendship relations to himself. However, each of those alters need to confirm

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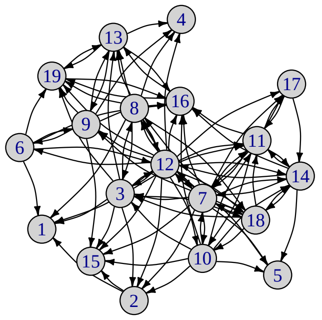
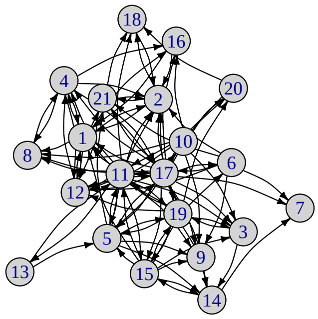
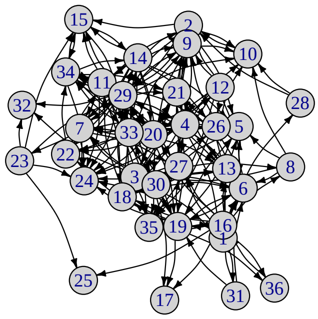


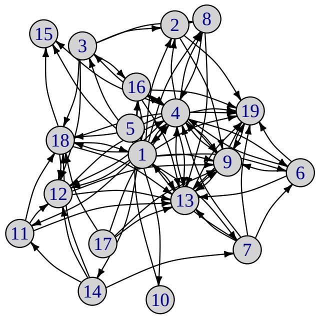
(A) *Pharma-Friendship*



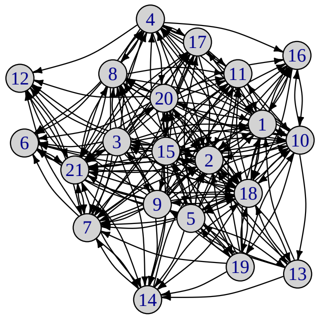
(B) *HighTech-Friendship*



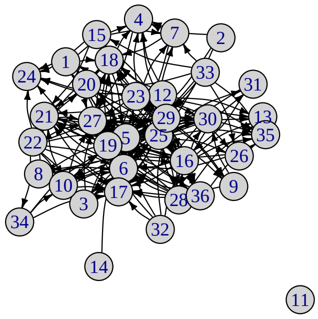
(C) *SilSys-Friendship*



(D) *Pharma-Advice*



(E) *HighTech-Advice*



(F) *SilSys-Advice*

FIGURE 4.7: *Reductions of advice and friendship on all datasets using RLAS method.*

that they do regard the person a friend for it to be recorded.

4.2.2.2.4 ULAS ULAS is the least restrictive of the LAS methods, since it only needs either the sender or receiver to perceive the relation for it to exist. This might not seem helpful at first, but consider the search for evidence of relations rather than the need for confirmed relations. Substantively, advice is a good example of such a relation. If i states that he/she seeks advice from j, j does not need to confirm the advice seeking behaviour for it to exist. Inversely, if j perceives i to seek advice from j, i does not need to confirm the behaviour, it can be confirmed that j perceives him/herself as being sought for advice, regardless whether it is confirmed by the seeking party. The researcher can thus generate evidence of a relation or interaction by relying on both parties in the dyad to offer evidence.

The LAS methods are helpful when the researcher is interested in reducing the CSS data into an aggregate of private assumptions of the network. If the researcher is more interested in the public assumptions of the network, the methods from the next section are more applicable. The reductions for the two relations on the three datasets are in Figure 4.10.

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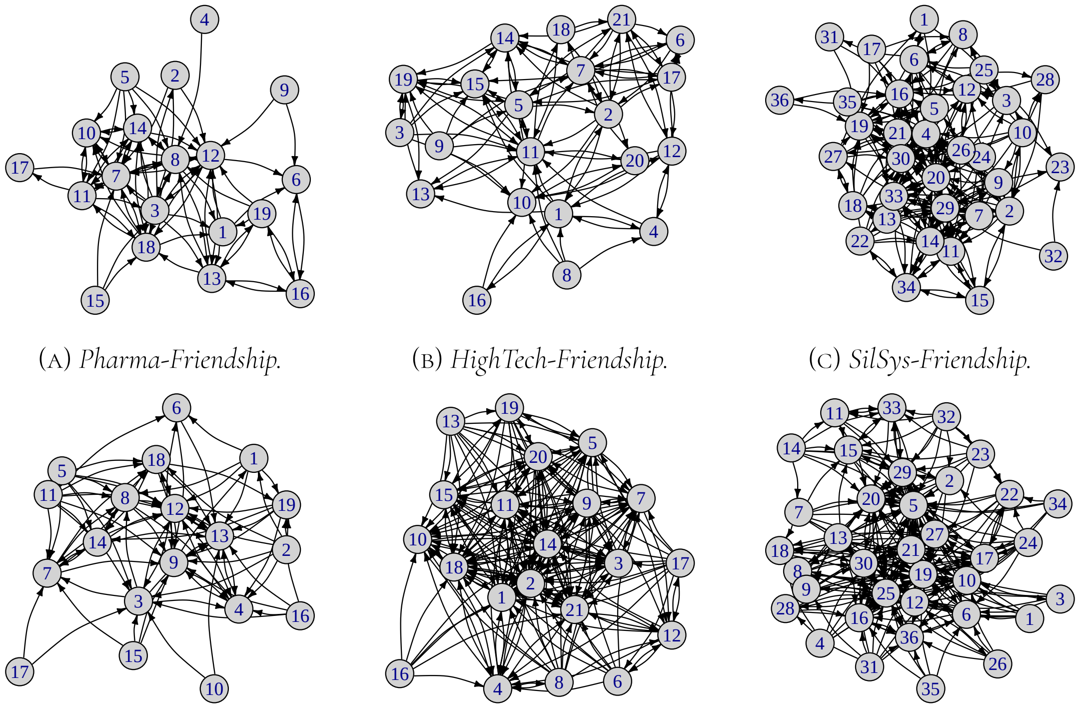

(A) *Pharma-Friendship.* (B) *HighTech-Friendship.* (C) *SilSys-Friendship.*

(D) *Pharma-Advice.* (E) *HighTech-Advice.* (F) *SilSys-Advice.*

FIGURE 4.8: *Reductions of advice and friendship on all datasets using CLAS method.*

4.2.2.3 Consensus Methods

Consensus methods practically ignore the private dyadic assumptions of the respondents by seeking a global perception. If the prominence of the perception of a relation is of interest, regardless of its veracity, then there are three methods to use; global aggregate (GA), global aggregate with a threshold function (GAT); and the adaptive threshold method (ATM). Each will be discussed in more detail below.

4.2.2.3.1 Global Aggregate Krackhardt (1987*a*) does not differentiate between global aggregate (consensus structures as he labels them) and global aggregate with a threshold, but the difference validates a distinction here. The original form of the consensus structure method is the same as the GAT method in the next section. This section explains a simpler form.

The GA method aggregates the perceptions of all respondents without a threshold. The result is, therefore, a valued digraph. The operation is simply the sum of all the slices:

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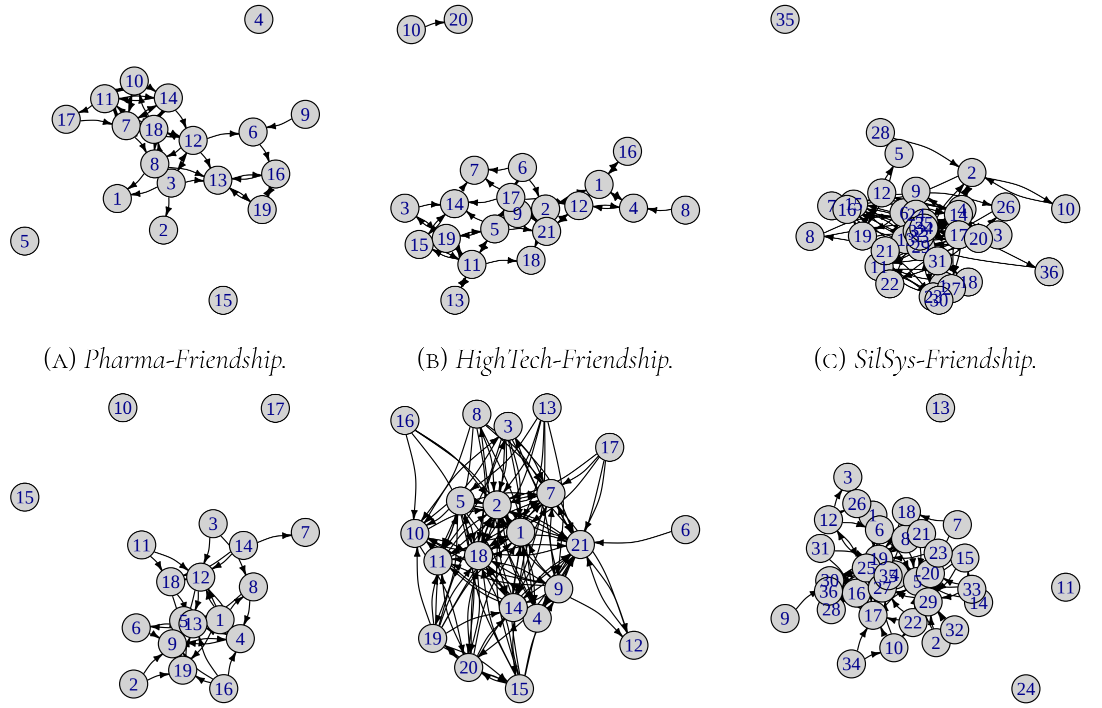

(A) *Pharma-Friendship.* (B) *HighTech-Friendship.* (C) *SilSys-Friendship.*

(D) *Pharma-Advice.* (E) *HighTech-Advice.* (F) *SilSys-Advice.*

FIGURE 4.9: *Reductions of advice and friendship on all datasets using ILAS method.*

$\mathscr{R}'_{i,j} = \sum_{k=1}^{n} \mathscr{R}_{i,j,k}$. The result indicates the degree to which a network, as a whole, perceives a relation. Figure 4.11 consists of weighted sociograms as a result of this method.

Although the thickness of the arcs are scaled according to weight in Figure 4.11, the sociograms remain difficult to interpret. There are options to reduce the noise of the GA procedure. One option is to only keep arcs that have a weight above a certain threshold. A relation might only be of interest if it is mentioned at least by 30% of respondents. This extension is precisely what Krackhardt (1987*a*) foresaw in including a threshold function. However, the threshold function, as presented by Krackhardt (1987*a*) dichotomises the result after applying the threshold. There might be some cases where it is more desirable to keep the weighted result, since 90% is markedly more than 51%, and the researcher might want to preserve the degree to which i is considered a friend of j.

4.2.2.3.2 Global Aggregate with Threshold Instead of investigating the degree to which a relation is perceived in public, the GAT method captures the veracity of a degree given a threshold of respondents agreeing to it. Krackhardt (1987*a*) settled on 50% as the threshold

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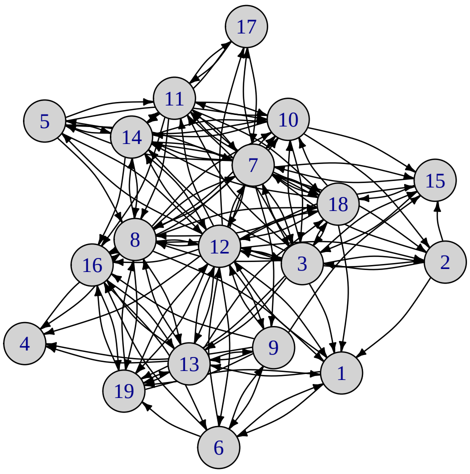
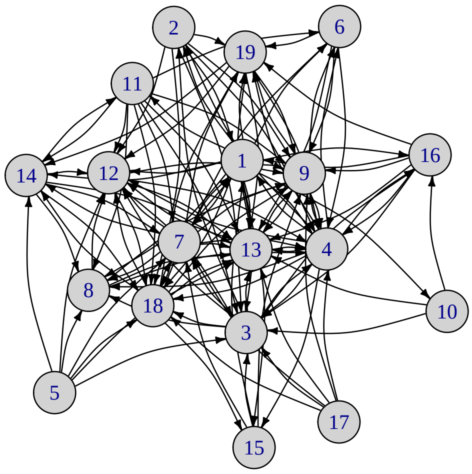
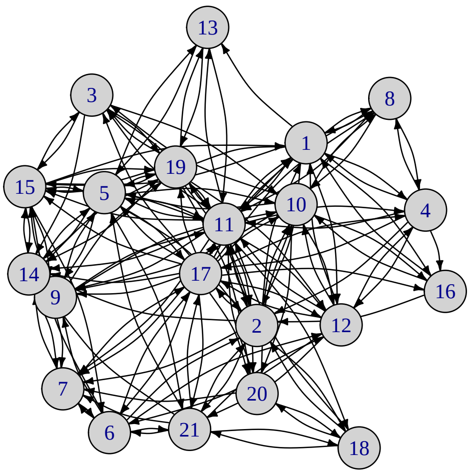


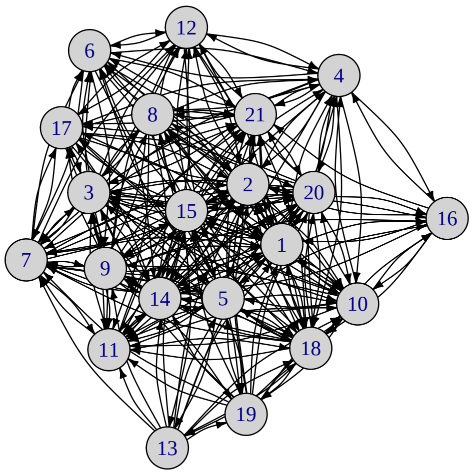
(A) *Pharma-Friendship.*



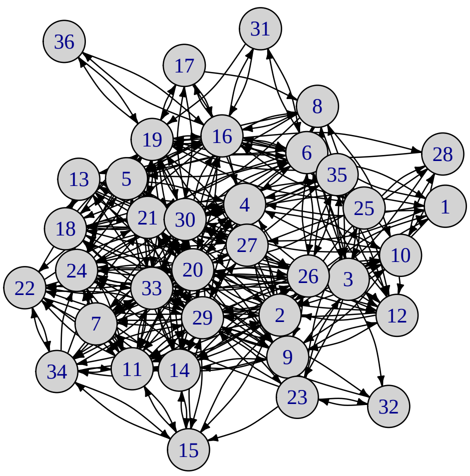
(B) *Pharma-Advice.*



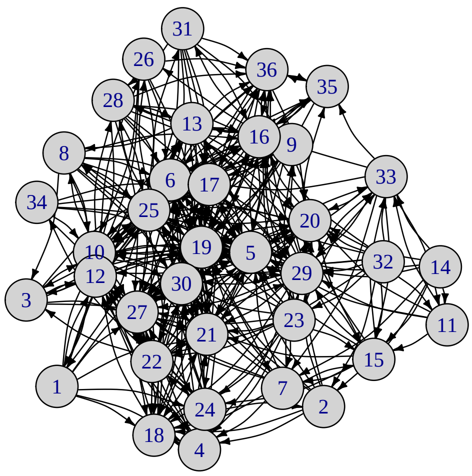
(C) *HighTech-Friendship.*



(D) *HighTech-Advice.*



(E) *SilSys-Friendship.*



(F) *SilSys-Advice.*

FIGURE 4.10: *Reductions of advice and friendship on all datasets using ULAS method.*

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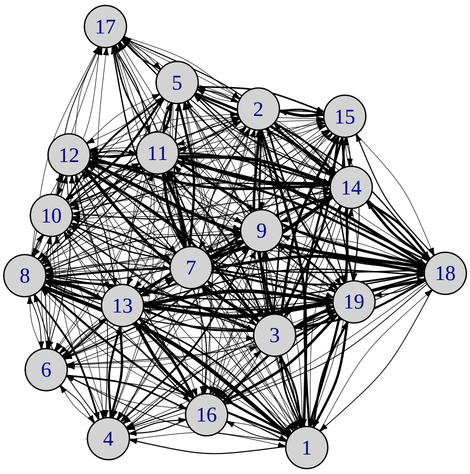
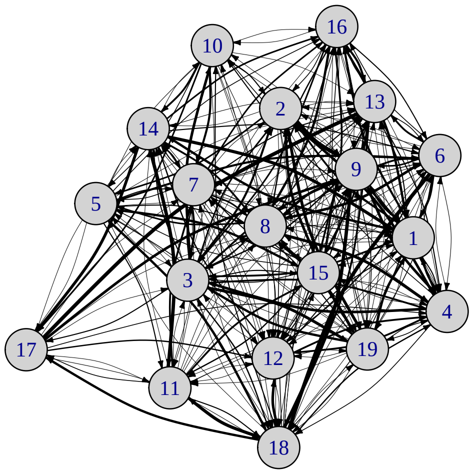
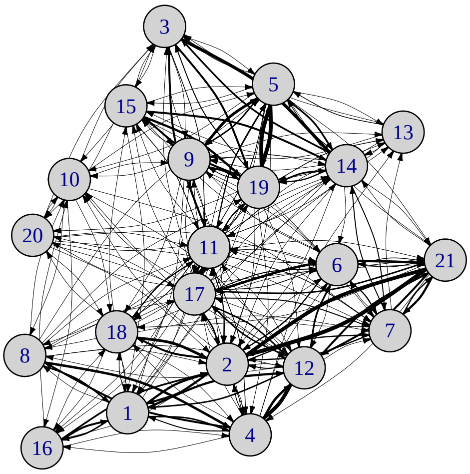


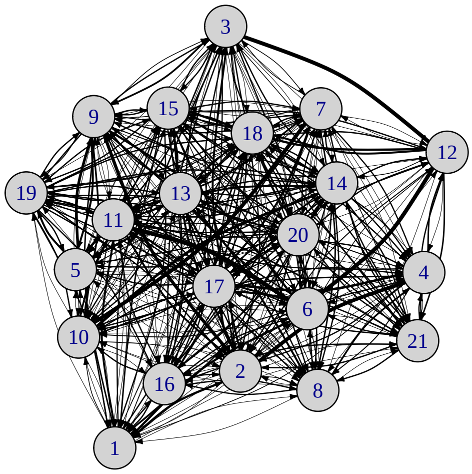
(A) *Pharma-Friendship.*



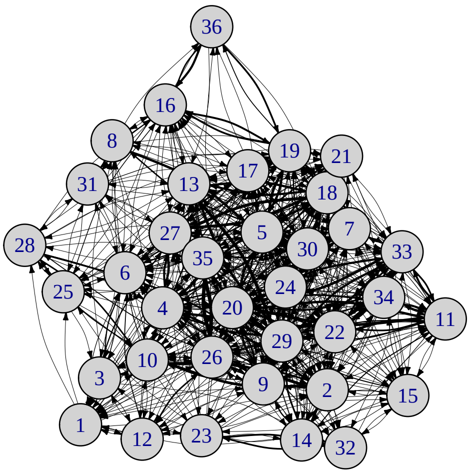
(B) *Pharma-Advice.*



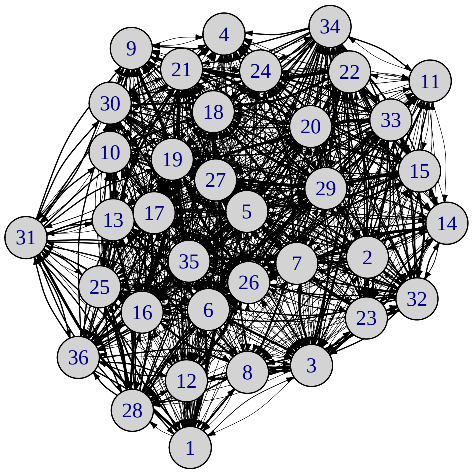
(C) *HighTech-Friendship.*



(D) *HighTech-Advice.*



(E) *SilSys-Friendship.*



(F) *SilSys-Advice.*

FIGURE 4.11: *Reductions of advice and friendship on all datasets using global aggregate method.*

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to dichotomise the data.

If there is reason to suspect that respondents will hide a private relation from the researcher, this method can be used to survey the opinions of the network at a lower threshold. Krackhardt (1987a) describes the following method to gain a GAT, where t is the threshold value between 0 and 1.

$$\mathcal{R}'_{i,j} = \begin{cases} 1, & \text{if } \frac{1}{n}\sum_{k=1}^{n} \mathcal{R}_{i,j,k} \geq t, \\ 0, & \text{otherwise.} \end{cases}$$

The sociograms in Figure 4.12 are the result of the GAT method with t =0.5.

In Figure 4.12, the method tends to produce low density networks with more isolated nodes compared to previous methods.

A key limitation to this method is the decision of where to set the threshold. The process is arbitrary, unless the researcher bases the threshold on some contextual rationale. Some solutions do exist to reach a threshold. For instance, a more appropriate threshold might be the average value of all arcs as derived by the GA method, therefore, setting t to the mode of the actual data. The adaptive threshold method (ATM) from Siciliano *et al.* (2012) offers a more guided process to set the threshold. The next section discusses this method.

4.2.2.3.3 Adaptive Threshold Method The intention of the ATM was to apply to a sample dataset that could infer a full CSS dataset (Siciliano *et al.*, 2012, p. 588). Nevertheless, the method can be used for a full CSS dataset.

By focussing on type 1 errors, or errors of commission,[2] Siciliano *et al.* (2012) devised a way to calculate an acceptable level of t. They offer the following procedure (Siciliano *et al.*, 2012, p. 589):

1. Set α, the tolerable error rate. Typical values are 0.05, 0.10, 0.15.
2. Draw a random sample of slices of size n from the CSS data.
3. Find the smallest k such that $\hat{\alpha}_k < \alpha$ and denote this by k'.
4. Compute the estimated network using the GAT method with the threshold k'.

$\hat{\alpha}_k$ is:

$$\hat{\alpha}_k = \frac{\text{number of Type 1 errors commited by the sample}}{\text{number of possible Type 1 errors in the sample}}$$

[2]Type 1 errors are commited when and individual percieves a relation to exist where there is none.

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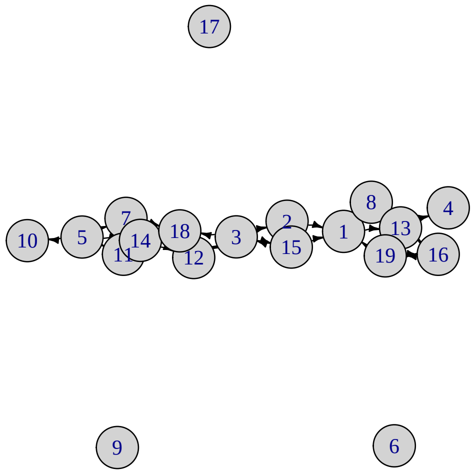
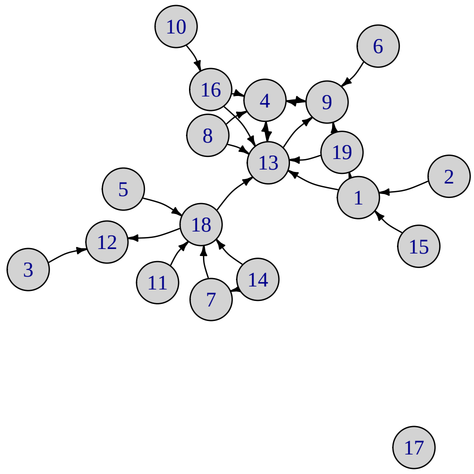
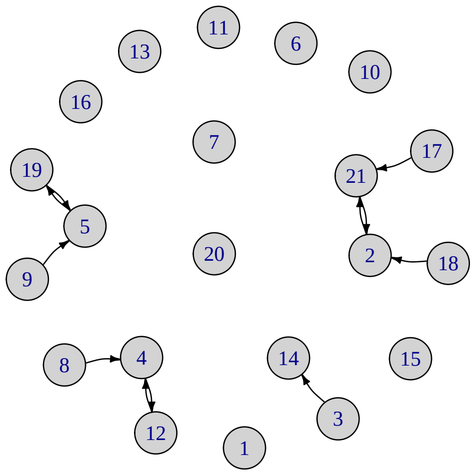


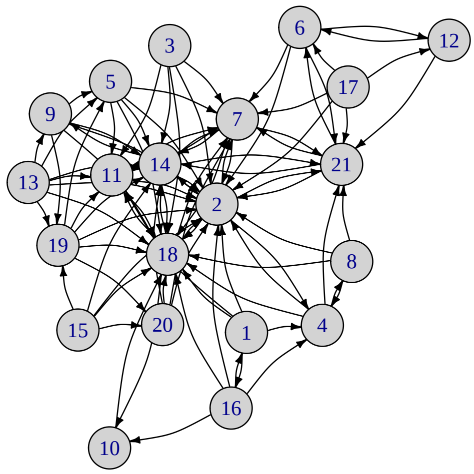
(A) *Pharma-Friendship.*



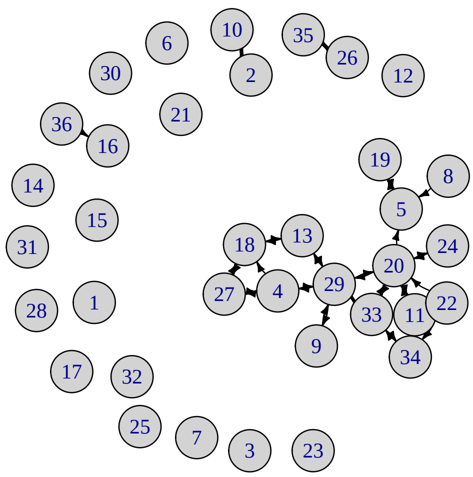
(B) *Pharma-Advice.*



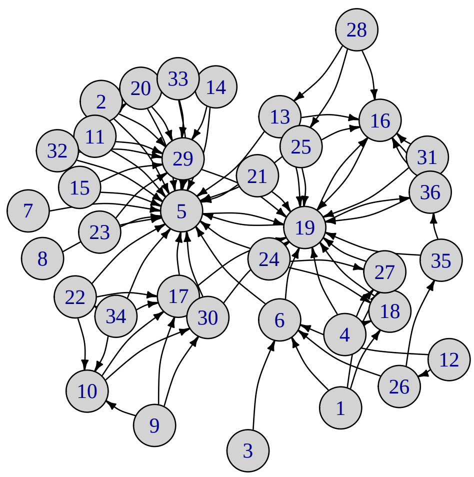
(C) *HighTech-Friendship.*



(D) *HighTech-Advice.*



(E) *SilSys-Friendship.*



(F) *SilSys-Advice.*

FIGURE 4.12: *Reductions of advice and friendship on all datasets using global aggregate method with threshold.*

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This method offers an informed and less arbitrary threshold, compared to other aggregation methods. ATM makes assumptions of experts outside of the private dyadic relation based on error types, while other aggregation methods are not concerned with an expert, but rather the consensus from the network. The ATM tries to take account of some committing more, or less, type 1 errors than others, and include this in the reduction to a single network from the CSS data.

The ATM, as devised by Siciliano *et al.* (2012), makes the assumption of knowledge and opinion, where the sender, i, and receiver, j, has knowledge of the tie, but the rest only have an opinion of the relation. This is a well-founded assumption and will hold true for many relations of interest. However, knowledge of relations might not be solely in the domain of the sender or receiver. This is especially true when issues with survey instruments are highlighted. A particular individual might misinterpret the question and it would, therefore, be better to rely on the whole group to indicate the general pattern of relations. More substantively, it can be argued that where $k \neq i$ or j, it might offer better judgements of the relation. For instance, a domain expert would be better able to judge relations between people than the people themselves. Consider a teacher who must judge academic superiority on certain domains between students. The students can be acceptable judges for when their peers are superior or inferior, but only the teacher can ultimately make the judgement as to the patterns among the students. Indeed, the teacher sets the bar to which the relational construct is measured. Even if it is not the intention to seek the experts, one might want to avoid weighing spurious responses equal to more informative responses. This intuition underpins the expert methods in the next section.

4.2.2.4 Expert Methods

Similar to the ATM, expert methods work with the intuition that certain individuals are more accurate than others in their judgement of the network. There are two broad approaches; the first ranks the respondents and weighs their opinion accordingly; the second defines a more nuanced domain expert. The former is the reweighing methods (single and iterative reweighing) and the latter, the Romney-Batchelder (RB) method and principal component analysis (PCA). These methods are more appropriate when it is not clear to the researcher which assumptions of viewpoint domination are applicable. For instance, when using LAS methods, the researcher has a choice in determining whose viewpoint, sender or receiver, should dominate in reducing the data-structure. With the following methods,

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there are thus two objectives, first, finding individuals whose view should dominate, and then reducing the network based on those identified individuals.

4.2.2.4.1 Single and Iterative Reweighing The simple intuition is that some respondents are closer to the consensus than others, and should, therefore, be weighted accordingly. Therefore, the general motive is to compare all slices to a criterion graph, and score each respondent according to how close or far they are from the criterion. These scores then become the weights of the next iteration of generating the central graph. This process either stops at this point (for single reweigh), or it iterates until some convergence level is satisfied.[3]

The first step of this process is trivial; defining the criterion network as the mean response of all respondents. The mean response is similar to the GAT method from the previous section. Banks and Carley (1994) specifically used the *central graph* as the criterion, but it is practically the same as GAT.[4] There is no reason why a researcher cannot use any of the other methods to generate the criterion graph, and such a novel attempt is yet to be implemented, but it is not the objective here.

The second part of the process is to measure the distance of each respondent to the criterion graph. Banks and Carley used *Hamming* distance, then used a *bin* procedure to group respondents according to their distance from the criterion. Butts (2016) used a graph correlation as measure of distance in their R implementation of the procedure.

This procedure can be altered, but the intuition remains the same; keep the perspective of those closer to the consensus, while removing the influence of those furthest from the consensus. Butts (2016, p. 42) confirms the intuition through explaining the single reweighing as an "*expertise weighted vote*".

As mentioned, the criterion graph can be generated in multiple ways. One such alternative is to do a PCA. The next section elaborates on this approach.

4.2.2.4.2 Principal Component Analysis This method, as implemented by Butts (2016), is similar to the single reweigh method above, but instead of using graph correlation or central graph and Hamming distance, they apply a *spectral decomposition* to the matrices to

[3]The single and iterative reweighing methods will only be covered on a practical level here. For a more technical treatment see Banks and Carley (1994) and Butts and Carley (2001).

[4]A central graph is the mean of all slices in a CSS dataset.

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find its canonical form. The first principal component scores can be used as weightings for the individual perceptions as with the previous methods.

The motivation for this method is that the first component, given that it is sufficiently contrasted with the rest in explaining the variance, produces a common theme from the perspectives (Butts and Carley, 2001, p. 39). If there is more than one dominating component, there will be an equal number of themes, none of which can individually explain enough of the variance in perception, but still closely captures some underlying theme in the data. This leads to an archetypal graph for subsets of respondents.

It is helpful to do *scree plots* for the three datasets including the friendship and advice relations. The plots are shown in Figure 4.13. Using an eigenvalue of 1 as a rule of thumb in identifying the number of components to keep,[5] at least three components qualify in the advice relation. In other words, there are three qualifying archetypes that capture distinct information about the network. For friendship, there are consistently four components above the threshold. Interestingly, the size of the network does not seem to have a noticeable effect on the number of components in the advice relation. However, there is a difference between the smaller Pharma and HighTech datasets and the larger SilSys dataset related to friendship, where the second and third components seem more prominent in the smaller networks than the larger. As such, there are some archetypical features present in the second and third component in smaller networks that disappear in larger networks. What those features are, is beyond the scope here.

4.2.2.4.3 Romney-Batchelder Method The Romney-Batchelder method is similar to the reweighing methods and PCA, with a slightly different motivation. The method originates in the work of Romney *et al.* (1986) and has subsequently received substantial attention. Romney *et al.* (1986) originally developed the method to assess answers to a test without an answer key, but other applications quickly became evident in cultural consensus work, where there is no answer key, only the culturally nuanced answers of people.

Different domains have interpreted this line of work, but most relevant here is the work of Borgatti and Halgin (2011*a*). Borgatti and Halgin (2011*a*) specifically applied these methods to SNA and included procedures in software packages UCINET and ANTROPAC.

[5]The threshold of 1 eigenvalue is known as the Kaiser-Guttman rule that is a rough rule to determine which components should be considered.

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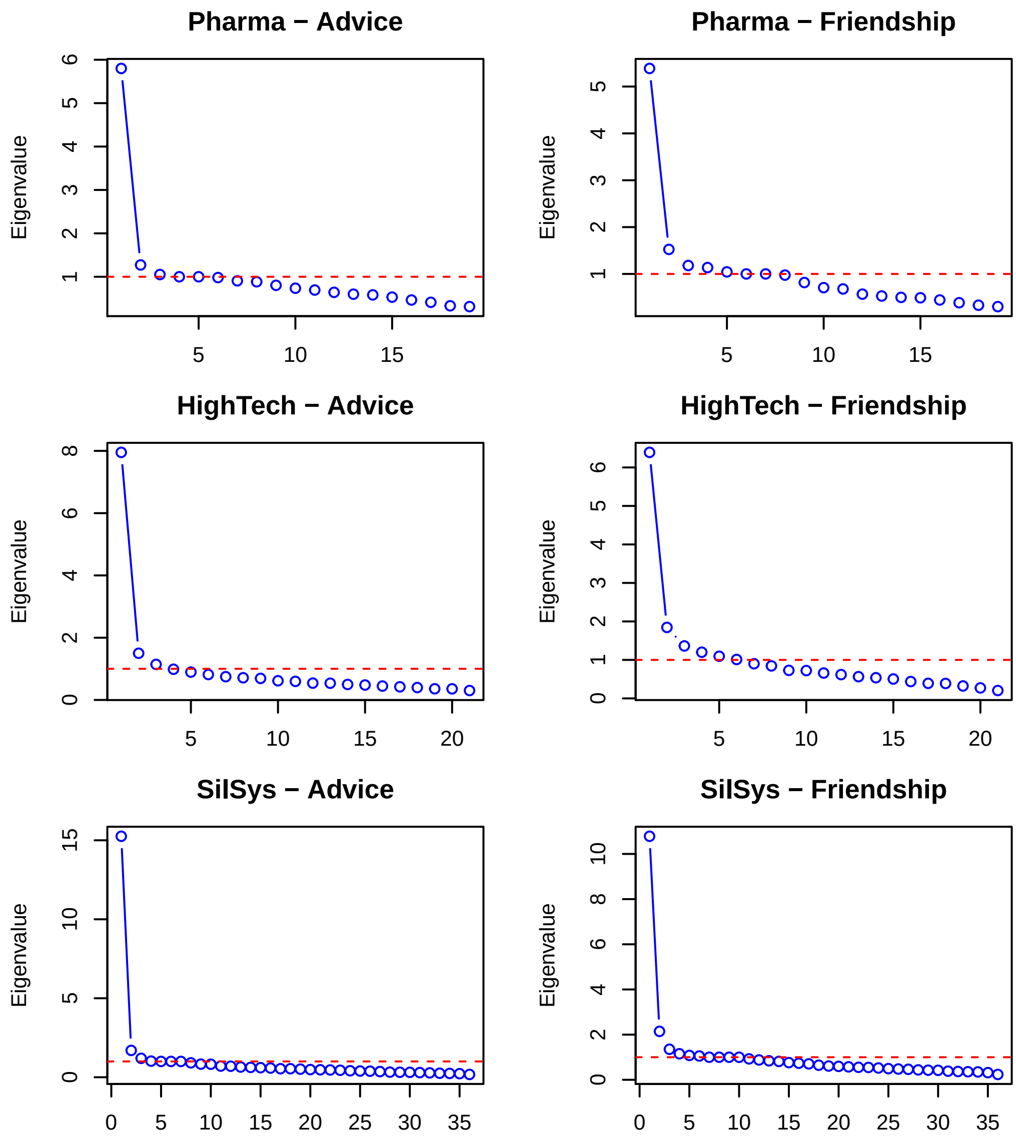

FIGURE 4.13: *Scree plots for all datasets on advice and friendship.*

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It is reasonable to expect that individuals who are embedded in a culture, will have varied competence of the unwritten rules and nuance of the culture. The expectation is that two people might have equal competence in their sensitivity to cultural norms, yet, are embedded in different cultures within the network. Therefore, varied answers offer two vectors of variance: competence and culture. If culture can be controlled, cultural competence can be measured. People can be expected to converge around a cultural truth or norm, but still vary in their competence about truth. One way to identify a cultural truth is through factor analysis. The cultural model has three key assumptions:

1. **A common truth**: There must be a correct answer.
2. **Conditional independence**: One student's answer is independent of another.
3. **Item homogeneity**: The questions must be relevant and of the same difficulty level.

Given these assumptions, the responses should converge on a shared response by the majority. However, as discussed above, this shared response does not consistently materialise. Therefore, the assumptions do not invariably hold. This method offers a reduction, based on a cultural consensus, and enables the identification of sub-cultures.

Consider again the scree plots in Figure 4.13 to test the validity of the cultural model. The first component dominates sufficiently to qualify for the cultural model. There is, however, evidence of a weak latent cultural domain, especially on the friendship relations, where four components are above an eigenvalue of one, compared to the advice relation, which produced three—marginally above the threshold.

The methods in this section offer a survey of reduction methods, although not all are applicable here, but the options are important to understand the eventual choice of a reduction method. These methods offer a single square matrix, distilled from a collection of perspectives of respondents. The next section will discuss the methods to analyse social networks that are usually presented as two-dimensional square matrices.

4.3 Network Measures

The previous sections investigated, in detail, how to reduce a CSS dataset. These methods vary from a basic slice, to more elaborate cultural models. Two-dimensional matrices make basic descriptive statistics possible. Descriptive statistics describe properties of either the network or nodes in the network. Given a single network there are many possible proper-

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ties. Table 4.6 presents an example of the descriptive statistics of the advice and friendship relation slices for respondent 2 in the HighTech dataset.[6]

TABLE 4.6: *Descriptive statistics of respondent 2's slice in the HighTech dataset.*

	Advice	**Friendship**
Nodes	21.00	21.00
Average Degree	10.48	2.00
Max Degree	23.00	8.00
Min Degree	3.00	0.00
Diameter	6.00	5.00
Mean Distance	1.93	2.45
Density	0.26	0.05
Reciprocity	0.27	0.67
Transitivity	0.57	0.12

Only considering the advice relation in Table 4.6 delivers scant insight. Descriptives need to be read in context. By adding the descriptives of the *friendship* network, more insight can be gained. For example, respondent 2 perceives higher connectivity in the advice network than in the friendship network, since the average degree (average count of connections of nodes) is much lower for friendship than advice. It is confirmed by the density metric. It can be inferred that respondent 2 perceives friendship relations to be more discerned than advice seeking behaviour. Moreover, respondent 2 also perceives friendship relations to be more reciprocated than advice, which makes sense, since both parties need to engage in a friendship for it to exist, but the same is not needed for seeking advice. Lastly, respondent 2 perceives advice relations to be much more transitive than friendships, but this might be an artefact of the high and low attributed density for the two relations.

It is impossible, from the above, to know whether all respondents share this perception. To do this, all perceptions should be calculated and compared to be able to determine whether these observations are more systematic, or merely descriptive of respondent 2. It is accordingly not possible to make broader inference from this one perspective. A question would be if the view of respondent two is an outlier, or whether it is part of a broader pattern in the perception of social relations. To identify a broader pattern, the descriptives

[6] All analyses were done using the *igraph* (Csardi and Nepusz, 2006) and *sna* (Handcock, Hunter, Butts, Goodreau, Krivitsky, Bender-deMoll and Morris, 2016) packages in R statistical software.

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of other respondents should be included and compared systematically. The next sections, while exploring analyses of networks, will attempt to illustrate such patterns by combining the metrics of all respondents. It is also important to highlight that this does not offer probabilistic statistical inference, since the patterns are not probabilistically tested.

The large number of available network measures make it impractical to exhaustively mention each here, and it is not the intent to focus on these metrics, since the next section on CSS network metrics is of more importance. Nevertheless, some measures are still important in this research project, and will be explored here. These metrics can be specified as graph level indices (GLI) and node level indices (NLI).

4.3.1 Graph Level Indices

GLIs indicate properties of a network as a whole. The most basic metric is the network size that is the count of the nodes in the network. Five key GLIs are highlighted: *density*, *reciprocity*, *transitivity*, *hierarchy*, and *centralisation*.

4.3.1.1 Density

Density is the count of edges as a proportion of possible edges in the graph. The maximum number of edges possible, is dependent on the number of nodes. To calculate density, let g be the number of actors in the network, and L the count of edges (Wasserman and Faust, 1994, p. 129). Calculating the density of a network results in a single measure for the whole network. Figure 4.14 reports the result of calculating the density of each slice in the three datasets. There are differences in the density for the HighTech and Pharma datasets, but not for SilSys. Density for the advice relation is higher in HighTech, but the same difference is not apparent with the other.

4.3.1.2 Reciprocity

Reciprocity measures the fraction of dyads that reciprocate a tie (Butts, 2008*a*, p. 27) i.e., what proportion of edges from $i \rightarrow j$ also have $j \rightarrow i$. Substantively, the question is; when i nominates j as a friend, did j nominate i? Friendship relations will be more reciprocated than advice, and the above graph confirms this. In all three datasets, individuals perceive higher reciprocation for friendship relations than for advice.

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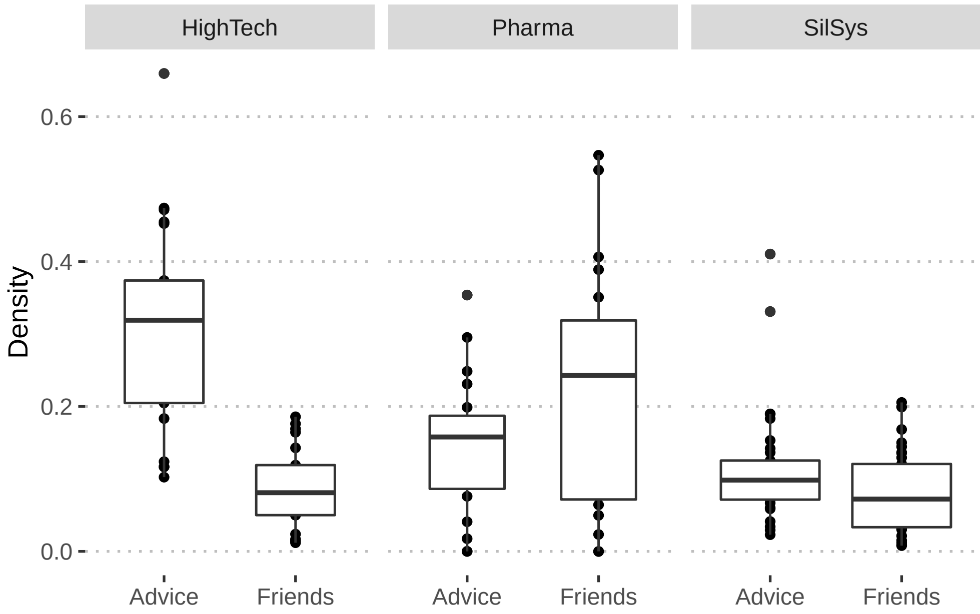

FIGURE 4.14: *Box-plots for density scores between advice and friendship relations, compared across datasets.*

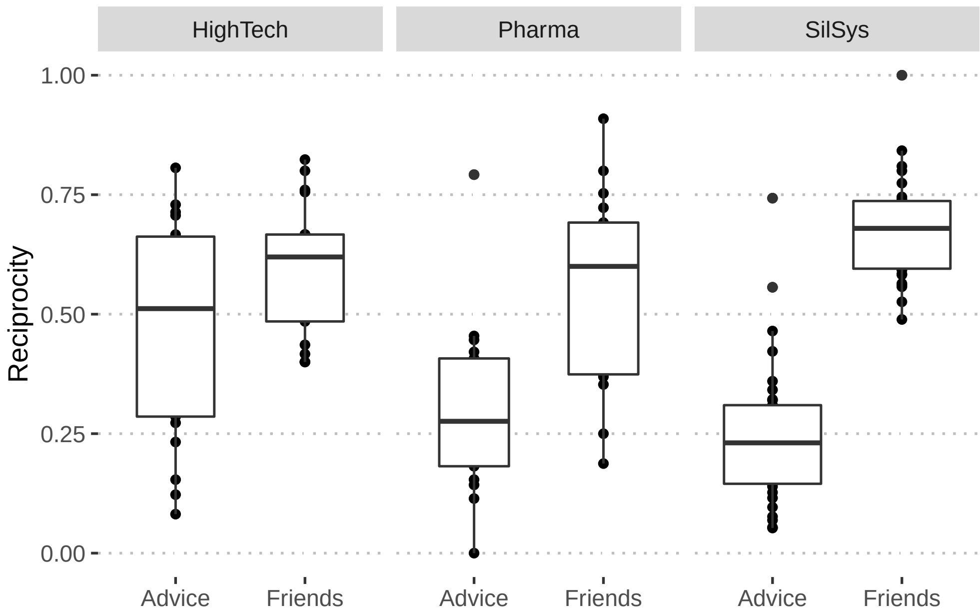

FIGURE 4.15: *Box-plots for reciprocity scores between advice and friendship relations, compared across datasets.*

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4.3.1.3 Transitivity

Transitivity considers all triads in a graph and the pattern of connection in each triad.[7] A relation is transitive if $i \rightarrow j$ and $j \rightarrow k$ always leads to $i \rightarrow k$. The simplest way to calculate transitivity is through matrix calculations, as proposed by Newman (2010):

Figure 4.16 plots the transitivity scores for each dataset by relational dimension; friendship and advice. The differences between advice and friendship are less pronounced than with reciprocity, but advice relations indicate higher transitivity than friendship, but only in the HighTech and SilSys datasets.

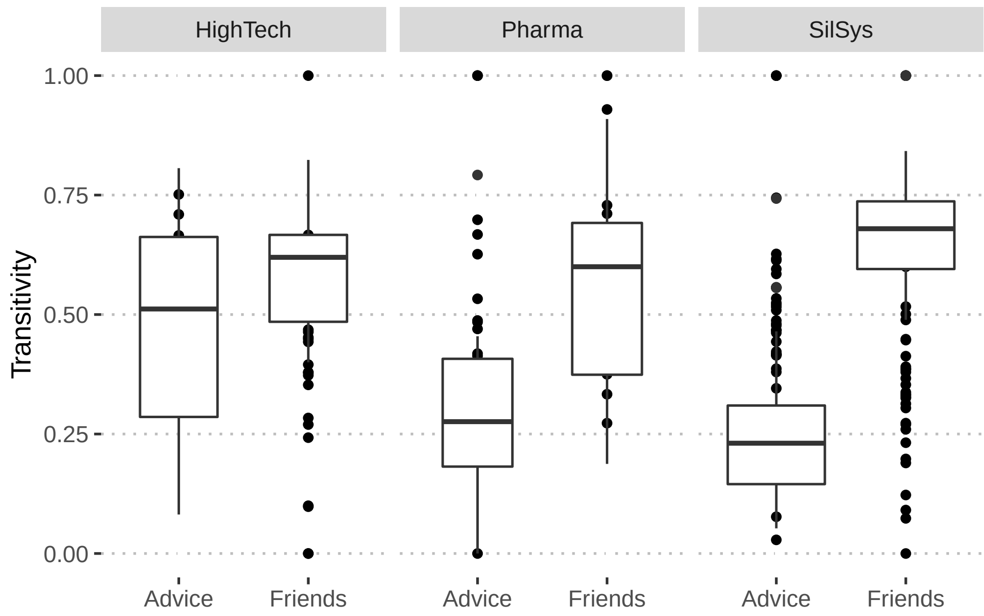

FIGURE 4.16: *Box-plots for transitivity scores between advice and friendship relations, compared across datasets.*

4.3.1.4 Hierarchy

Hierarchy is a measure developed by Krackhardt (1994) for the degree to which a social network tends toward a hierarchical structure. Taking the fraction of non-null dyads in the

[7]Transitivity is also referred to as *clustering coefficient*. The measures are the same, and the labels are thus interchangeable.

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reachability graph—which are asymmetric i.e., not reciprocated—determines the measure of hierarchy (Krackhardt, 1994, p. 97). Substantively, *"graph hierarchy is associated with the degree to which the organisation is dominated by status in its informal relations"* (Krackhardt, 1994, p. 102). Figure 4.17 plots the hierarchy scores of the three datasets for each relational dimension.

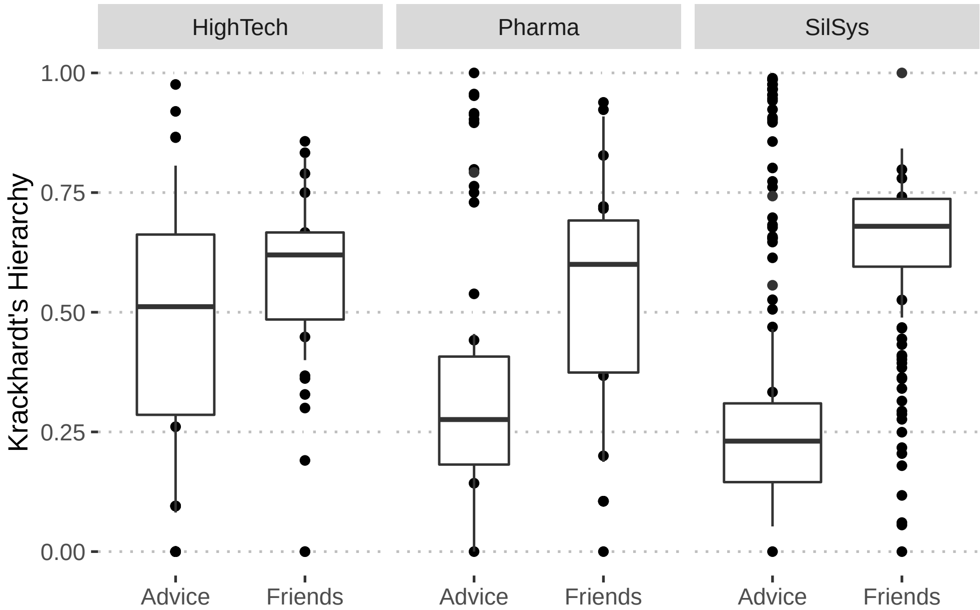

FIGURE 4.17: *Box-plots for hierarchy scores between advice and friendship relations, compared across datasets.*

Krackhardt (1994), posited that advice would result in higher graph hierarchy when compared to friendship. This is confirmed, but only in the SilSys Dataset. The difference is less pronounced in the Pharma dataset, and is reversed in the HighTech dataset.

4.3.1.5 Centralisation

Centralisation is an index of how centralised a graph is as a whole. Wasserman and Faust (1994, p. 117) offer a definition of group centralisation: when centralisation is 0, it means that all nodes have equal centrality, while centralisation approaching 1 indicates the dominance of individual nodes in the proportion of centrality. Figure 4.18 summarises the centralisation scores of the individual slices across the three datasets, while comparing the

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variance between advice and relation. From Figure 4.18 it is evident that people perceive advice relations to be more centralised than friendship.

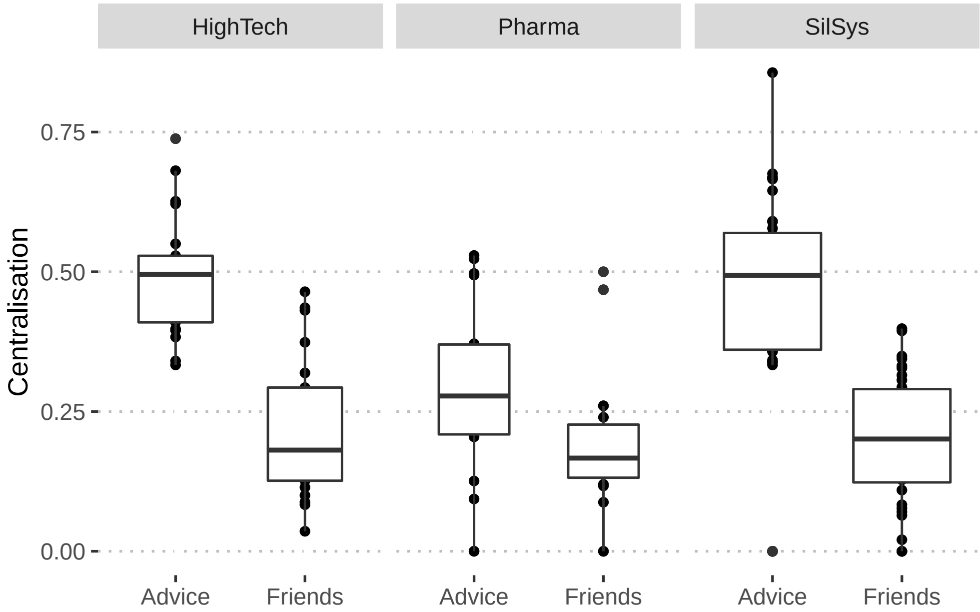

FIGURE 4.18: *Boxplots for centralisation scores between advice and friendship relations, compared across datasets.*

4.3.2 Node Level Indices

NLIs capture information of the nodes derived from the network as a whole. Centrality measures tend to dominate as a measure of nodes. In a review of centrality measures, Borgatti and Everett (2006) use the classification of *radial* and *medial* measures of centrality. Radial measures summarise the connectedness of the node with the rest of the network (Borgatti and Everett, 2006, p. 12). Whereas radial measures count the number of paths on which a node is a terminal point, medial measures count the number of paths where a node is an interior point. The next sections will briefly discuss two radial measures, namely indegree and eigenvector centrality, and two medial measures: betweenness and closeness centrality.

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4.3.2.1 Indegree centrality

Indegree centrality is the number of directed edges into a node as a proportion of directed edges into others. Dependent on the context, this measures the importance of the node. Indegree centrality is sometimes referred to as prominence, since it measures how many nodes *choose* the node in question (Wasserman and Faust, 1994, p. 172). However, if the question asked to choose the people you do not know or recognise, the reverse would be true. The substantive context is, therefore, important to consider when interpreting indegree centrality.

4.3.2.2 Eigenvector Centrality

Eigenvector centrality is the sum of a node's connections to alters, weighted by the alters' degree centrality. The intuition is that a node might not be well-connected itself, but be connected to other more well-connected alters. This is similar to being friends with the popular class-mate at school. Prell (2012, p. 101) offers a good example for the context here. Consider entering a new job. You do not know anyone, nor do you understand the social dynamics in the office. A good strategy would be to shadow or befriend a person that knows, or is friends with many people leading to faster access to meeting more people. This strategy increases eigenvector centrality. An algorithm is used to find the largest eigenvalue of an adjacency matrix, which is captured in detail elsewhere (cf. Borgatti and Everett, 2006; Prell, 2012; Wasserman and Faust, 1994).

4.3.2.3 Betweenness Centrality

Betweenness centrality is frequently likened to *control* in the network (Borgatti, 2005; Borgatti and Everett, 2006; Wasserman and Faust, 1994). Radial indices only consider direct connections between nodes, whereas medial measures, such as betweenness, introduce the idea that, if not directly connected, nodes placed between any two nodes mediate the interaction along the network. These nodes, potentially unknown to the nodes at the endpoints, can control the interactions or flow of information. In other words, between any two non-adjacent nodes—assuming they are they can reach each other through a path—there is a node that can break the path at will. Betweenness centrality is, therefore, an important measure in networks since it intuitively captures the idea that single nodes can have a large impact on the network as a whole. Betweenness centrality is, therefore, derived from the

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network as a whole and not just direct adjacency. It is calculated by taking count of the geodesic paths a node is on (Prell, 2012). A node on the highest proportion of geodesic paths has the highest betweenness centrality. A geodesic path is the shortest path between any two nodes, i and j (Wasserman and Faust, 1994, p. 110). Wasserman and Faust (1994, p. 190) offer an formula for calculating betweenness centrality.

4.3.2.4 Closeness Centrality

Closeness centrality is another example of a medial centrality measure, since it indexes nodes, based on their position between non-adjacent alters. It is similar to betweenness centrality, but it does not look at the proportion of geodesics on which a node is located, but rather indexes nodes (i) based on their geodesic distance from all other nodes (j). Nodes with high betweenness centrality will have a high probability of having access to something travelling between any random geodesic from $i \to j$. Nodes with high closeness would, on average be the first mediating node on any random geodesic from $i \to j$. An interesting benefit of such a position is that it consumes the least amount of energy to reach any other node in the network. Wasserman and Faust (1994, p. 184) offer an index calculation for closeness centrality.

4.4 Conclusion

The objective of this chapter is not to offer an extensive survey of methods available to the researcher to analyse social networks. The focus is on methods to reduce three-dimensional datasets into a form that can be used to apply standard SNA. Network measures discussed in this chapter are by no means unique to CSS data, but can be implemented on a two-dimensional socio-matrix. There are no unique measures for CSS data, except the graph reduction methods discussed earlier in this chapter. However, a key advantage of CSS data is that it offers multiple perspectives of the same network. These perspectives can be used to define a true network, against which each respondent can be measured. This measurement is their social acuity that is the only NLI or GLI unique to CSS datasets. Nodes can, therefore, be measured both on their centrality and social accuracy. Networks as a whole can likewise be measured on their centralisation and congruence. The next chapter will specify the applicable reduction methods and acuity measures, as well as the NLIs and GLIs needed in the particular context.

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CHAPTER 5

ANALYSIS AND FINDINGS

Chapter 3 introduced the idea that humans are embedded in social networks. They are reliant on the collective and individual ability to understand and navigate these social networks to sustain society. It is a troubling discovery that humans are inaccurate about social interactions surrounding them. With more scrutiny, it becomes apparent that some individuals are more accurate than others in their judgement of their complex social environments. The initial thought by scholars was that people who are in certain favourable positions, reap advantages in uncovering the arrangements of social relations in which they are embedded. Being central in a network, some argue, offers a person access to more information about their social network than is the norm for their peers. But, Chapter 3 challenges this intuition . The key challenge is that if people in favourable positions within social networks gain network acuity from their position, then a formalised version of such a position should carry with it remnants of acuity benefits. This logical extension does not exist in empirical work. Prior work found either a negative relationship, or no relationship between formal social position and social network acuity. Even accepting the negative relationship, along with the forwarded explanation, the problem remains.

People with a formal social position do not have to exert the same efforts to monitor and understand patterns of social interactions. If correct, then an observed negative relationship should prevail between social position and network acuity, at least sometimes. It is sensible to expect that informal network restructuring would not directly lead to a formal position, but it can improve informal positions. Therefore, it is in the interest of those in informal positions, more than for formal, to remain updated with the surrounding social networks. However, even formal positions, allowed time and considerate fluidity in social network patterns, have an interest in monitoring social networks, even if in a more abstract manner.

A set of hypotheses are therefore introduced that to argues for the relation between informal social position and acuity to be reversed. This is because SNC acuity enables individuals to position themselves into more favourable network positions. Since no definite resolution exists on the key relationship between formal social position and network acuity, the issue was still problematic. An empirical investigation would help resolve this by con-

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firming the proposed hypotheses. Chapter 4 introduces the options for gathering the social network data needed. It highlights the procedural options for preparing and analysing the data. The aim of this chapter is to report on the actual execution of the chosen method, and testing the proposed hypothesis against the empirical results.

5.1 Introduction

Recall the three key hypothesis H1a, H2a and H3a. H1a expects no significant correlation between formal position and SNC acuity. H2a proposes no significant effect on informal positions by formal positions. Finally, H3a hypothesises no significant effect on informal social position by social network acuity.

Recall that the aim of the hypotheses is to find evidence that social network acuity leads to informal social position. H1a must be confirmed, while H2a, and H3a must be rejected for H2b and H3b to confirm the overall argument.

To test these hypotheses, there are three groups of variables to extract from the data; *social position* measures; *acuity* measures; and, general model *controls*.

Measurements for social position are of two kinds: (1) informal position measures—indegree, eigenvector, betweenness, proximal betweenness and constraint—and (2) formal position measured by organisational hierarchy. The control measures are a collection of GLIs: density, reciprocity, transitivity, hierarchy, and centralisation. Acuity measures consist of interpersonal acuity—measured by S_{14}—and structural acuity, measured by structural graph correlation.[1]

The first step, however, is to create the criterion networks. These criterion networks will then be used to infer individual acuity.

5.2 Criterion Networks

Each dataset has two relational dimensions, advice, and friendship. Each relation requires a different reduction method. It is possible to apply the more advanced reduction methods such as iterative reweigh PCA. Yet, as will become clear, the simpler LAS methods would reduce the network to a criterion to measure SNC acuity.

[1] See Section 3.7 for a discussion of the two measures of acuity.

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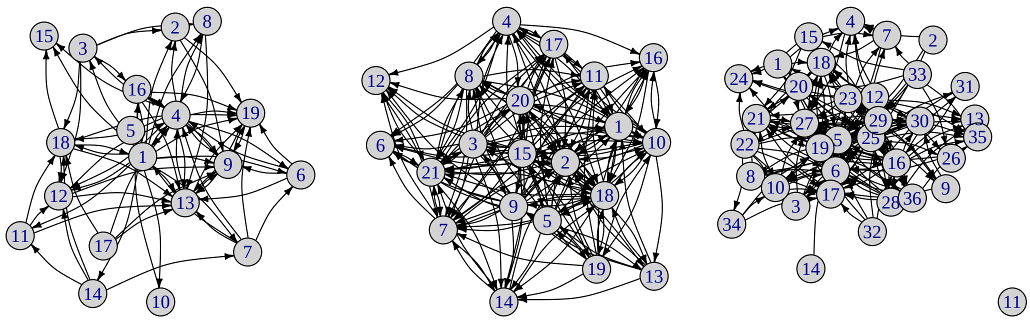
The aim of the criterion network is to create a 'truth' from the perspective of the authoritative respondent, or respondents, on a particular relation.[2] As an example, using one of the expert methods to define the criterion, the resulting acuity of individuals will reflect their competence compared to the experts in the network.

By utilising a consensus method, the resulting acuity would be a measure of how well an individual is congruent with the consensus of the network. Respondents offered their *version* of the truth relative to the alter they responded about. Keeping this in mind, the next two sections expand on the methods chosen for each relational dimension. The next two sections will thus argue for a specific reduction method for each relational dimension.

5.2.1 Advice

Asking respondents to indicate *who would go to who for advice* on work-related matters established the advice relation. Accordingly, an arc from $i \rightarrow j$ would show that i seeks advice from j. The criterion to deduce whether a relationship exists only relies on the sender (i) of the advice tie. The person being sought for advice does not control who comes to them for advice they might only know who approaches them. Since seeking behaviour is of concern, it is reasonable to define the criterion by the sender, therefore leading to a row-dominated (RLAS) method as the reduction method for this relation.

Figure 5.1 contains the plots of the three resulting networks. Table 5.1 summarises the graph level descriptive statistics of each criterion network.



(A) *Pharma advice criterion.* (B) *HighTech advice criterion.* (C) *SilSys advice criterion.*

FIGURE 5.1: *The advice criterion networks for the three datasets.*

[2]The notion of truth is of course relative here, since the researcher has no definitive way of defining it. It is nevertheless a helpfull shorthand to use the concept of 'truth', in stead of some contrived qualified concept.

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Figure 5.1 does not distinguish the central actors, particularly Figure 5.1b and Figure 5.1c. Therefore, Table 5.2 shows the extract of the central vertices according to three centrality measures; indegree, betweenness and eigenvector. In both Pharma and HighTech the same person has the highest indegree and eigenvector. In SilSys, node 19 is the highest both in betweenness and eigenvector. The GLIs in Table 5.1 indicate the overall differences between the three datasets. The HighTech dataset has the highest density at 0.45, mostly explained by a high average degree (18.10). HighTech also has the highest reciprocity and transitivity. This is important to note when collapsing the three datasets into one. To isolate the effects between independent and dependent variables, requires controlling these measures.

TABLE 5.1: *Advice criterion networks: graph level indexes.*

	Pharma	**HighTech**	**SilSys**
Nodes	19	21	36
Max Degree	21	32	29
Min Degree	0	9	0
Average Degree	8.32	18.10	10.89
Diameter	4	3	7
Mean Distance	2.02	1.64	2.57
Density	0.23	0.45	0.16
Reciprocity	0.33	0.47	0.18
Transitivity	0.54	0.73	0.44

NOTE: All graph measures are normalised.

TABLE 5.2: *Advice criterion networks node level indexes: most central nodes.*

	Pharma	**HighTech**	**SilSys**
Indegree	13	2	5
Betweenness	4	18	19
Eigenvector	13	2	19

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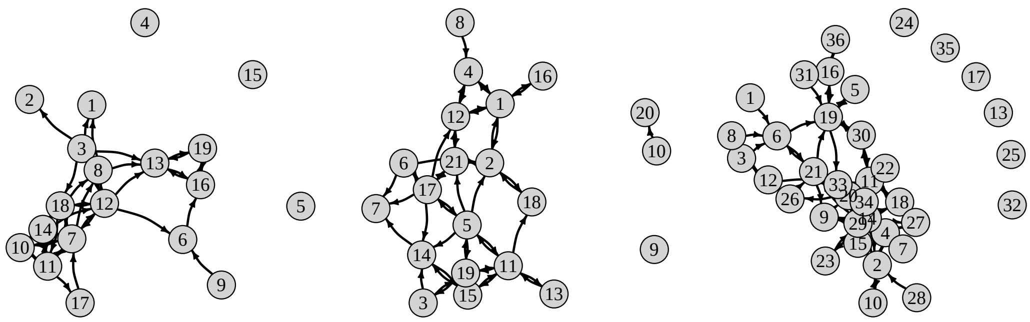
5.2.2 Friendship

Asking respondents to answer who considers whom a friend, elicits the friendship relations.[3] Therefore, a relation $i \rightarrow j$ indicates that i considers j a friend. To reduce the dataset into a single criterion network, there are two options. The preferred method would again be RLAS, since the interest is the individual's perception of friendships, whether it is reciprocated. However, as with previous research, notably Krackhardt (1990), it might be better to be more conservative with estimating a friendship relation. This can be for two reasons; first, people might over-report their friends and this method reduces the validity; second, if both parties agree that the relation exists, there is a higher chance of being an enduring perception.[4] For this reason, to establish a criterion the ILAS method is used . The resulting sociograms of this method is in Figure 5.2a. The resulting networks are less dense, and there are more isolated nodes. To confirm this, Table 5.3 summarises the GLIs of each network. The density is lower than advice for all datasets. Reciprocity is higher than for advice, from 0.33 to 0.57 for Pharma, 0.47 to 0.75 for HighTech and 0.18 to 0.73 for SilSys.



(A) *Pharma friendship criterion.* (B) *HighTech friendship criterion.* (C) *SilSys friendship criterion.*

FIGURE 5.2: *The friendship criterion networks for the three datasets.*

Table 5.4 captures the nodes with the highest centrality measures. None of the central individuals in the advice network are also central in the friendship networks. The same pattern, of the same individual, for both indegree and betweenness for Pharma and HighTech

[3]The three datasets have different phrasings, but the effect was to elicit who people consider as friends.

[4]Note, it does not mean it confirms the relationship in both directions. This method helps confirm that relation $i \rightarrow j$ is reported by both i and j. This does not mean that when $i \rightarrow j$, then $j \rightarrow i$.

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TABLE 5.3: *Friendship criterion networks: graph level indexes.*

	Pharma	HighTech	SilSys
Nodes	19	21	36
Max Degree	12	9	24
Min Degree	0	0	0
Average Degree	4.84	4.86	5.50
Diameter	4	7	6
Mean Distance	1.98	2.95	2.76
Density	0.13	0.12	0.08
Reciprocity	0.57	0.75	0.73
Transitivity	0.54	0.28	0.37

NOTE: All measures are normalised except: nodes, maximum degree, minimum degree, and diameter.

TABLE 5.4: *Friendship criterion networks node level indexes: most central nodes.*

	Pharma	HighTech	SilSys
Indegree	7	2	29
Betweenness	12	17	29
Eigenvector	7	2	29

is repeated here, but, a single individual scored highest in all three measures in the SilSys dataset.

With the two criteria created, it is prudent to discuss the variables of interest. The next sections are divided into independent and dependent variables, with a third section covering general control variables. The independent variables are interpersonal acuity, structural acuity, and formal position. Dependent variables are indegree, eigenvector, betweenness, proximal target betweenness and constraint. The control variables are graph size, hierarchy, transitivity, reciprocity, centralisation and density, each calculated for both the slice, and the criterion networks.

Before the variables are discussed in the next sections, consider again the argument proposed in Chapter 3. Figure 5.3 offers a visual representation of the hypothesis interaction for the argument. The proposition follows that social position is the result of SNC acuity. To confirm this, the dependent variable should be social positions, and the independent should be SNC acuity. To confirm the direction, an additional independent variable, formal position, should also have an effect on social position. The next section will elaborate in

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the independent variables.

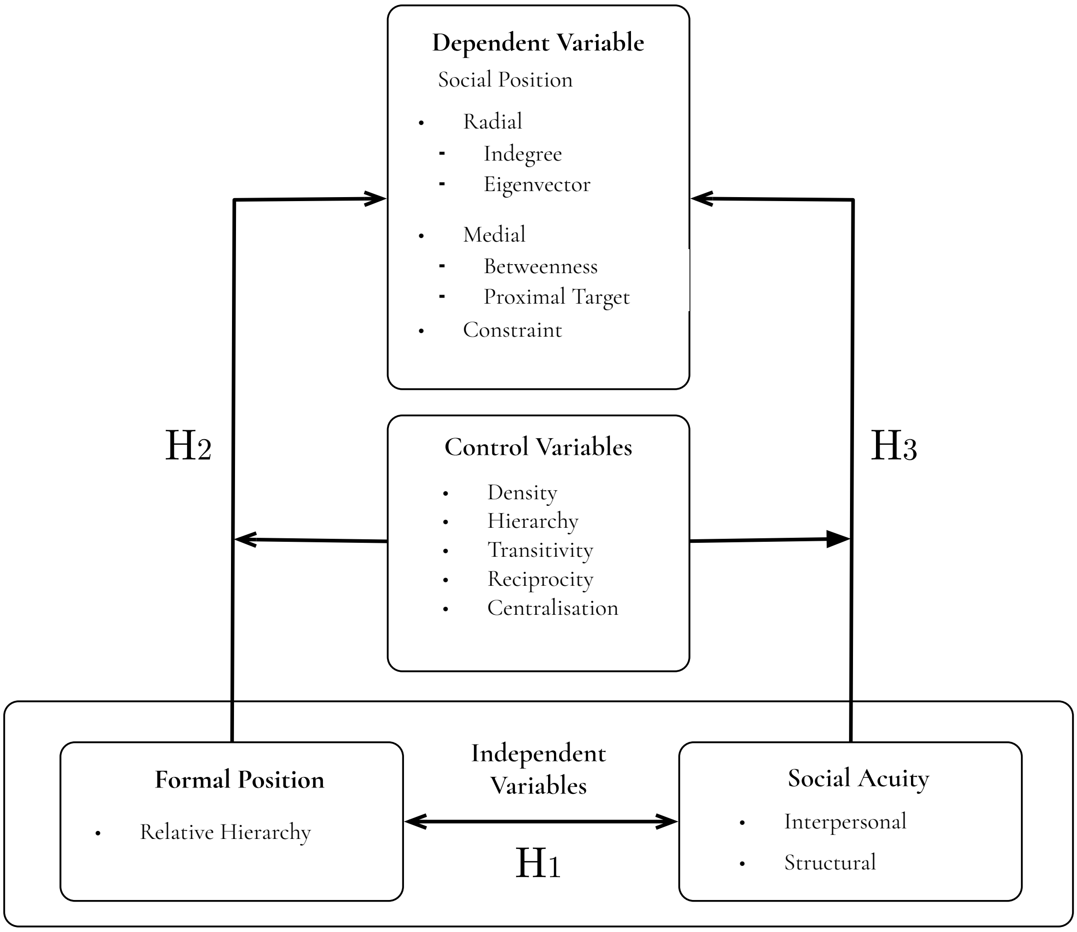

FIGURE 5.3: *Hypothesised model.*

5.3 Independent Variables

There are two independent variables: formal position that is measured by the organisational hierarchy; and SNC acuity that is measured through interpersonal and structural acuity. The next section discusses SNC acuity.

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5.3.1 SNC Acuity

With the two criterion networks, each respondent's slice can be measured against the criterion. In Chapter 3 structural acuity was introduced as a distinct enough measure, compared to interpersonal acuity, to include in the concept of general SNC acuity. Both measures will, therefore, be calculated and included as SCN acuity measures.

A Pearson-moment graph correlation is used to calculate interpersonal accuraccy.[5] The structural acuity measure is calculated through a Pearson-moment structural correlation as proposed by Butts and Carley (2001) and implemented in the.[6] Structural acuity builds on the premise: if any two dyads randomly swap places, the structure should generally stay the same. The correlation is, therefore, not for interpersonal acuity, but rather for an underlying structural pattern. The two measures should converge to 1, since, someone who is perfectly accurate about all dyadic relations, will necessarily have to be accurate structurally.[7]

The aim is, therefore, to identify those who might be interpersonally inaccurate, yet structurally accurate. Dyadic affiliations between people might elude an individual's memory, but they might be able to use culturally appropriate schemas to infer the relational dimensions between any two dyads. For instance: if the dominant organisational culture is not to be friends with superiors, then a respondent—who knows of this cultural norm—will apply it in the case between John and his line manager Jane, where they don't know for sure whether they are friends, they will then confidently state no friendship relation. A simpler form is when people assume that in a particular network everyone is friends with everyone that leads to a denser network. If this perception is true, then the respondent should have reasonable structural accuracy, while knowing few dyadic relations. Another example: people might not know specific dyadic relations, but be aware of an overall structure of two clusters. The respondent will, therefore, report the two clusters, but neglect to report specific dyadic relations. This structural intuition is a more realistic and enduring assumption of relational patterns in organisational contexts. It is, therefore, important to include this as a measure of overall SNC acuity. The descriptive statistics for the results are in Table 5.5.

From Table 5.5 overall structural acuity μ= 0.46 is higher than overall interpersonal acuity μ= 0.34, with respondents being almost equally accurate on advice relations (interpersonal: μ= 0.34, structural μ= 0.46) and friendship relations (interpersonal: μ= 0.33,

[5] All calculations were done using R, and the *sna* package (Butts, 2008*b*).
[6] The *sna* package was used for structural graph correlations (Butts, 2016).
[7] The inverse is, however, not true.

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TABLE 5.5: *Descriptive statistics for acuity measures.*

Measure	Relation	Dataset	N	Mean	SD	Min	Max
Interpersonal			152	0.34	0.09	0.07	0.52
	Advice		76	0.34	0.08	0.08	0.50
		HighTech	21	0.31	0.06	0.21	0.43
		Pharma	19	0.29	0.10	0.08	0.48
		SilSys	36	0.39	0.06	0.21	0.50
	Friendship		76	0.33	0.10	0.07	0.52
		HighTech	21	0.36	0.11	0.09	0.52
		Pharma	19	0.32	0.11	0.10	0.47
		SilSys	36	0.33	0.08	0.07	0.48
Structural			152	0.46	0.08	0.19	0.63
	Advice		76	0.46	0.07	0.24	0.60
		HighTech	21	0.43	0.06	0.31	0.52
		Pharma	19	0.46	0.10	0.24	0.60
		SilSys	36	0.47	0.06	0.35	0.55
	Friendship		76	0.47	0.09	0.19	0.63
		HighTech	21	0.48	0.09	0.30	0.61
		Pharma	19	0.47	0.09	0.31	0.63
		SilSys	36	0.47	0.08	0.19	0.60

structural μ= 0.47). It is beneficial to combine the three datasets to offer a generalisation over contexts,Table 5.5 however offers a breakdown of the descriptive statistics by subsetting the data into relations (advice and friendship) and datasets (Pharma, HighTech, & SilSys).

5.3.2 Formal Positions

The proposed hypotheses include two types of social position, formal and informal. The measure of formal position is discussed in this section.

The intention of formal position is to measure an individual's position in a formal social structure in the organisation. There are multiple ways to achieve this, a routine method would be to use the formal organisational hierarchy. The organisation hierarchy formally assigns social roles, which carry advantages, responsibilities, and expectations of the people

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filling certain positions. The higher an individual is placed in the organisational hierarchy the more social advantages they would have. These advantages can be divided into power and status, as means of exerting influence on others (Fragale, Overbeck and Neale, 2011). *Power* is gained through the control of resources within the structure. Traditionally, the interaction process in a hierarchy prohibits skipping levels, either up or down. This offers each individual at each level a certain control over certain resources, since they act as the only access point to resources. Examples of resources are monetary resources or information. The benefit of *status* is that it offers intangible benefits such as the reduced need to tender for acceptance of authority or opinion. If an individual has higher status, it signals that their opinion or objectives should take preference in the immediate group where they have higher status.

These advantages are similar to advantages of informal social positions such as centrality as discussed in Section 5.4.1.

Annotating individuals with their position in the hierarchy records their formal position (hierarchy) measure. The lowest value is the lowest position in the hierarchy, whereas the highest value is the highest position. What is important to preserve from the hierarchy information is the ordinal property of the levels.

Since the three datasets will be compared in later analysis, the measures should be converted into relative measures, since they are on an ordinal scale. This is done by taking the ordinal value divided by the maximal position. The resulting relative measures should all then have a minimum of 0 and a maximum of 1, where 0 is the lowest position in the particular organisation, and 1 the highest. Table 5.6 reports the summary statistics for both the absolute and relative values of the formal position measures.

In contrast to formal social positions, informal social positions are socially developed and reinforced through interaction in an organisation. More generally, these positions are not likely to be formally recorded, yet they are fairly well understood by social participants. Various layperson concepts embody such social positions, such as *social ladders*, the *in-group*, or the *guru*. There are multiple ways to measure such positions in the informal organisation social life. A promising measure of social importance is centrality measures. The next section will, therefore, highlight four centrality measures, two of each of the radial and medial classifications of Borgatti and Everett (2006), and a measure of network constraint by Burt (2001).

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TABLE 5.6: *Descriptive statistics for measures of formal position.*

Measure	Relation	Dataset	N	Mean	Median	SD	Min	Max
Formal Position								
	Absolute		75	2.055	2.000	1.053	1.000	5.000
		HighTech	21	2.714	3.000	0.561	1.000	3.000
		Pharma	19	2.579	3.000	1.261	1.000	5.000
		SilSys	35	1.333	1.000	0.645	1.000	3.000
	Relative		75	0.425	0.500	0.422	0.000	1.000
		HighTech	21	0.857	1.000	0.280	0.000	1.000
		Pharma	19	0.395	0.500	0.315	0.000	1.000
		SilSys	35	0.167	0.000	0.323	0.000	1.000

NOTE: Taking the ordinal value divided by the maximal position calculates the relative formal position. The formal Position of one respondent in the SilSys dataset was not recorded, the N is therefore 35 instead of the usual 36.

5.4 Dependent Variables

The dependent variables for the proposed hypotheses are a collection of informal social network positions. There are multiple ways to express or measure such positions, but, the most intuitive are centrality measures. The intuition that central nodes in a network are important drives centrality measures (Borgatti, 2006). Since the central thesis suggests that individual agents with higher social network acuity would position themselves into favourable network positions, it would only be beneficial to measure such positions in the most intuitive measure available, instead of more advanced yet intuitively less palatable measures such as structural equivalence.

5.4.1 Centrality

The most often used metric of position in a social network is centrality (Borgatti, 2005). Centrality is frequently linked to some form of advantage to those who occupy the positions, usually through the theoretical motivation of social capital (Lin, 1999). The connection between being central in a network, and benefiting from such a position is intuitive. Various authors have linked centrality to substantive outcomes such as power (Bonacich, 1987), social influence (Ibarra and Andrews, 1993) and individual performance in organisations (Sparrowe, Linden and Kraimer, 2001). Network positions such as centrality are also intuitive for agents within a network, much of which is captured in concepts such as

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networking, where networking can be regarded as an attempt to increase contacts (degree centrality) or find and connect to strategic contacts (closeness or betweenness centrality).

Centrality measures of interest are; indegree, betweenness, eigenvector and proximal centrality. The rationale for inclusion and descriptive statistics of each measure follows in the sections below. Each of the measures were calculated on the criterion networks for each relation. This is because these networks offer the closest approximation of the individuals true positions. It would be nonsensical to derive centrality measures on a slice, since this would be a biased measure.

5.4.1.1 Indegree Centrality

Indegree centrality, or simply indegree, measures how popular a person is as a friend of others, or how many people seek this individual for advice. Kilduff and Krackhardt (1994, p. 95) considers indegree as a measure of prominence, since these people are the most prominent in others' cognitions of friendship and advice networks. Indegree is a simple, yet important measure of importance in a network. It measures the general quality of a nodes interconnectedness (Landherr, Friedl and Heidemann, 2010, p. 376) or the level of communication activity (p. 355 Mizruchi and Potts, 1998), and it is well established as a predictor of performance in organisations (Tasselli *et al.*, 2015, p. 1367).

Based on the criterion graph, as explained in Section 5.2, indegree centrality is calculated, and the results are shown in Table 5.7.

TABLE 5.7: *Descriptive statistics for indegree measures.*

Measure	Relation	Dataset	N	Mean	Median	SD	Min	Max
Indegree			152	0.039	0.031	0.033	0.000	0.152
	Advice		76	0.039	0.033	0.033	0.000	0.152
		HighTech	21	0.048	0.047	0.021	0.021	0.095
		Pharma	19	0.053	0.038	0.043	0.000	0.152
		SilSys	36	0.028	0.018	0.030	0.000	0.117
	Friendship		76	0.039	0.030	0.034	0.000	0.130
		HighTech	21	0.048	0.059	0.031	0.000	0.098
		Pharma	19	0.053	0.043	0.041	0.000	0.130
		SilSys	36	0.028	0.020	0.027	0.000	0.101

NOTE: The indegree centrality measures are rescaled to sum to 1.0 on each relation within each dataset.

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Since the centrality measures are rescaled, it is difficult to interpret individually.[8] Nevertheless, it is evident in Table 5.7 that the results are similar across the three datasets and relations. The mean is larger than the median, which indicates positively skewed centrality distribution as expected from social network data (see Newman, 2010, p. 243).

5.4.1.2 Eigenvector Centrality

Eigenvector centrality is a measure of a node being connected to well-connected others. Among all the measures, eigenvector is perhaps the most strategic centrality measure for an individual to aim for if they were to position themselves. Considering that popularity (indegree) or a position between others (betweenness) is more difficult to control directly, placing oneself close or relative to central others might be a prudent strategy. This idea is captured well in the *basking in reflected glory* effect (Kilduff and Krackhardt, 1994). The basking in reflected glory effect is the advantage one gains from being close to a successful alter in a network, creating the perception of similar success. For example, being friends with a popular person will increase popularity, at least in the perception of others. Eigenvector centrality is highly correlated with indegree centrality (Valente, Coronges, Lakon and Costenbader, 2008, p. 20) in general, but still offers the opportunity to distinguish from normal centrality and eigenvector in certain situations.[9]

When considering the issue of network flow, and the manner of flow influencing the centrality measure; eigenvector centrality is the applicable measure for information flow in the network, particularly advice, since it does not assume that information flows only on the shortest path, or that the resource is mutually exclusive—i.e. parallel duplication, rather than serial duplication (Borgatti, 2005).

The summary statistics of the eigenvector centrality measures are shown in Table 5.8.

5.4.1.3 Betweenness Centrality

Taking the shortest path between all nodes and counting the number of times a node is on the path calculates betweenness centrality (see Freeman, 1979). The node is, therefore, considered to be *between* others. The advantage of this position is the ability to control the flow of information between mediated nodes. In cases where the flowing network resource

[8] For reference, the unscaled measures are used earlier in Section 4.3.

[9] If the measures show high multicollinearity, there are certain steps, such as dimension reduction strategies that could be employed to combine the two measures.

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TABLE 5.8: *Descriptive statistics for eigenvector centrality measures.*

Measure	Relation	Dataset	N	Mean	Median	SD	Min	Max
Eigenvector			152	0.039	0.030	0.039	0.000	0.152
	Advice		76	0.039	0.034	0.039	0.000	0.152
		HighTech	21	0.048	0.047	0.023	0.018	0.097
		Pharma	19	0.053	0.043	0.048	0.000	0.152
		SilSys	36	0.028	0.008	0.039	0.000	0.136
	Friendship		76	0.039	0.029	0.039	0.000	0.141
		HighTech	21	0.048	0.056	0.034	0.000	0.101
		Pharma	19	0.053	0.031	0.047	0.000	0.141
		SilSys	36	0.028	0.015	0.033	0.000	0.108

NOTE: The eigenvector centrality measures are rescaled to sum to 1.0 on each relation within each dataset.

increases in value with accumulation (i.e., cash) betweenness would be appropriate. This is as opposed to the speed being more important than volume. As an example: an individual positioned between most other people would more frequently receive information, but possibly later than certain other nodes. Assuming the resource is gossip, a person with high betweenness centrality will most probably hear gossip if it is spreading, but it might be old gossip by the time it reaches them. This issue is well covered by Borgatti (2005).

Consider the two relations of interest—advice and friendship. Asking people who they go to for advice elicits the advice relations. Therefore, it can be assumed that information travels in the reverse order of the direction of the network. Those sitting between most others are then capable of controlling the flow of information. This control offers benefit to the node with high betweenness since the node can alter the information for self-serving reasons, or take part in rent-seeking behaviour. Less illicit motivations might be that the individual is regarded as an effective communicator and act as a translator within the organisation that is a sought after role from the organisation's perspective.

Centrality measures are based on the flow model of social networks (Borgatti, 2005; Freeman *et al.*, 1987). When considering a network built out of a relation that does not readily lend itself to the idea of flow in the network, centrality measures become problematic. Some measures, such as indegree, still have value since they are both structural and flow measures (Borgatti and Everett, 2006). Betweenness centrality is classified as a medial measure of centrality. In networks where relations are costly to build, betweenness will in-

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dex an ability to utilise the position for gain, or again from the network's perspective, these positions are valuable. Thus, when considering the friendship relation, it does not have an evident flow of anything as opposed to advice that flows from one to the next. Friendship relations can nevertheless offer conduits for the flow of multiple network resources, such as favours and trust. The summary statistics for betweenness centrality is in Table 5.9.

TABLE 5.9: *Descriptive statistics for betweenness measures.*

Measure	Relation	Dataset	N	Mean	Median	SD	Min	Max
Betweenness			152	0.039	0.005	0.070	0.000	0.420
	Advice		76	0.039	0.004	0.081	0.000	0.420
		HighTech	21	0.048	0.022	0.081	0.000	0.329
		Pharma	19	0.053	0.004	0.109	0.000	0.420
		SilSys	36	0.028	0.001	0.061	0.000	0.264
	Friendship		76	0.039	0.006	0.057	0.000	0.247
		HighTech	21	0.048	0.040	0.053	0.000	0.152
		Pharma	19	0.053	0.036	0.073	0.000	0.247
		SilSys	36	0.028	0.004	0.049	0.000	0.235

NOTE: The betweenness centrality measures are rescaled to sum to 1.0 on each relation within each dataset.

5.4.1.4 Proximal Betweenness

It should be considered, in an information exchange network, whether the source or the target of information has the ultimate control in utilising the information for personal gain. This is as opposed to the intermediates controlling the information flow, as assumed by standard betweenness centrality. Consider extreme examples. It is, usually, assumed that in an information exchange network, the source of information has value to the network, and can use the position for advantage, since the individual can control the information at the source. However, the target, where the information eventually ends up, might also have benefit in an information exchange network. Consider the triad $i \rightarrow k \rightarrow j$, where the direction of the arrow indicates the flow of information, where i gives information to k, who in turn gives information to j. The source is thus i and the target is j. Consider the option given by betweenness centrality, that k can decide to not pass the information

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on to j. The triad would then be $i \rightarrow k \quad j$ or $i \rightarrow k$, in which case k is now the target. It should be clear that a target of information in the network could be a bridge refusing to transfer information, thus filtering information available to j. In this case, k the target, does have advantage. It is, therefore, conceptually the same as the advantage for nodes high in betweenness centrality, however, this measures the actuality of the node exercising the ability not to pass on the information. This is a limited measure, since the node could just be an end node, with no-one seeking information from him or her.

Another way to interpret the difference in importance of source and target in information exchange is to consider the idea that when people offer advice, they do control what information is spread. However, those seeking advice have control over where they seek advice from and whether they think it is valid. This paints a picture of a self-filtering information environment. An example would be someone who has a superior, but difficult, solution to a problem. This individual will be the ideal information source. However, since the solution they offer might be difficult, many people might choose to ignore the advice in favour of an inferior yet easier solution from an alternate source. This choice bolsters the indegree of the alternate source above the superior source.

Considering advice, the ultimate source of advice relations has advantage, however, the position is probably a function of the person's knowledge, or even friendliness. Therefore, someone with a higher sense of the network structure might be the only person that knows who the ultimate authority for advice might be, and would, therefore, position themselves to be an intermediate. This individual can then control the information to the rest of the network. Brandes (2008) developed the measure of such a penultimate proxy, which defines both proximal source and target measures.

Since the target is the source of information, in advice relations, the proximal target measure should be used. Figure 5.4 is a sociogram example of a node (F) that has high proximal target and source betweenness centrality score. For the friendship relation, the proximal source measure is more appropriate. This is because the node is the penultimate gateway to resources mediated through friendship relations.

The descriptive statistics of the proximal target and source calculations are in Table 5.10.

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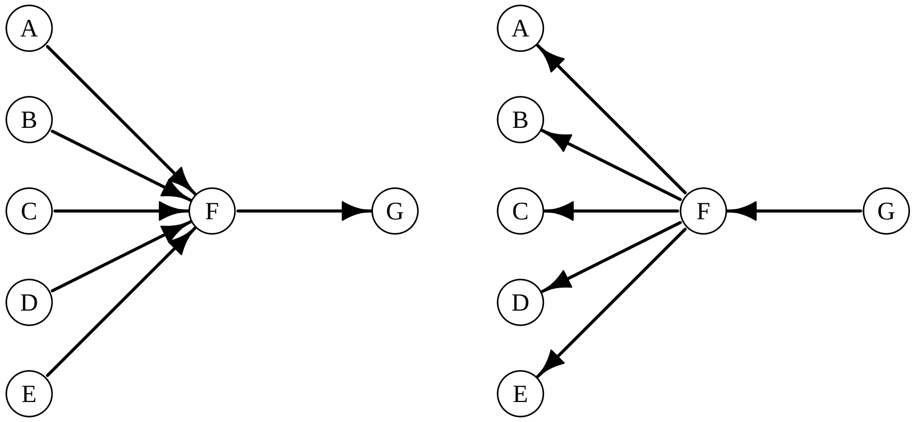

(A) *Sociogram example of a proximal target position.*

(B) *Sociogram example of a proximal target position.*

FIGURE 5.4: *Proximal betweenness variants.*

5.4.2 Constraint

Another measure to consider, which centrality measures do not fully capture, is constraint. The proposed argument highlights the possibility of social agents positioning themselves within informal social structures. Thus, agency may be used, not only to reach favourable positions, but to avoid detrimental ones. Therefore, including constraint as a measure of social position highlights the possibility of acuity, at the least, leading to an intuition of reducing ones own constraint within the network.

To understand constraint, a discussion on structural holes is appropriate. Structural holes is a key concept in the pursuit of understanding the social capital of network structures and positions (Burt *et al.*, 2013). Two key positions in the work of Burt *et al.* (2013) each lead to *bridging* and *bonding* capital leading to advantage. Burt *et al.* (2013) argues that there is more evidence for brokerage leading to advantage for both the individual and the network. However, earlier work did emphasise the possibility of both brokerage and closure being sources of competitive advantage to individual nodes or networks.

A network is more closed the denser it is. However, a more nuanced way of measuring closure is needed since a network can be broken up into dense clusters or cliques. Working from Coleman, Burt (2000, p. 351) highlights that the social advantage of a closed network is two-fold. *First*, any one node has multiple sources of information all of which have redundancy, so as to ensure stability in information sources. This also ensures that, if the

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TABLE 5.10: *Descriptive statistics for proximal betweenness centrality measures.*

Measure	Relation	Dataset	N	Mean	Median	SD	Min	Max
Proximal Target			152	0.039	0.004	0.069	0.000	0.409
	Advice		76	0.039	0.004	0.077	0.000	0.409
		HighTech	21	0.048	0.017	0.078	0.000	0.274
		Pharma	19	0.053	0.004	0.098	0.000	0.409
		SilSys	36	0.028	0.001	0.064	0.000	0.337
	Friendship		76	0.039	0.007	0.060	0.000	0.347
		HighTech	21	0.048	0.019	0.050	0.000	0.136
		Pharma	19	0.053	0.018	0.089	0.000	0.347
		SilSys	36	0.028	0.004	0.045	0.000	0.195
Proximal Source			152	0.046	0.005	0.110	0.000	1.000
	Advice		76	0.053	0.005	0.144	0.000	1.000
		HighTech	21	0.048	0.022	0.087	0.000	0.385
		Pharma	19	0.053	0.003	0.129	0.000	0.432
		SilSys	36	0.056	0.002	0.177	0.000	1.000
	Friendship		76	0.039	0.005	0.061	0.000	0.275
		HighTech	21	0.048	0.009	0.063	0.000	0.213
		Pharma	19	0.053	0.024	0.068	0.000	0.213
		SilSys	36	0.028	0.003	0.056	0.000	0.275

NOTE: The proximal centrality measures are rescaled to sum to 1.0 on each relation within each dataset.

network resource deteriorates over distance, information reaching nodes is clear. *Second*, closed networks offer security of surveillance, and, therefore, reduces the cost and risk of trust relations. People also communicate and collaborate more effectively in denser groups, as Burt *et al.* (2013, p. 529) states: *"People tire of repeating arguments and stories explaining why they believe and behave the way they do. Within a group, people create systems of phrasing, opinions, symbols, and behaviours defining what it means to be a member"*. Individuals embedded in such dense groupings of a network, therefore, have advantage over those who are not embedded in such a structure.

Opposed to the idea of the advantage of closure, is the argument that bridges lead to more advantage, or in the language of Burt, structural holes. Structural holes are structural gaps between clusters in a community, created by the absence of ties between the clusters.

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The advantage is not evident from the holes themselves but that they can be bridged by individuals, labelled bridges or brokers. These structural holes, therefore, enable the opportunity to span these holes between non-redundant clusters of information. The individual can thus take advantage of this position in two ways (1) be a source of novel information to the bridged clusters, or (2) control the flow of information between the clusters.

Calculating each node's constraint measures their level of brokerage (Burt, 2004, p. 362).[10] The higher the constraint measure, the less access the node has to structural holes. The summary statistics are in Table 5.11.

TABLE 5.11: *Descriptive statistics for constraint measures.*

Measure	Relation	Dataset	N	Mean	Median	SD	Min	Max
Constraint			152	0.402	0.327	0.248	0.132	1.000
	Advice		76	0.267	0.228	0.127	0.132	1.000
		HighTech	21	0.218	0.213	0.021	0.192	0.263
		Pharma	19	0.363	0.341	0.101	0.234	0.676
		SilSys	36	0.247	0.217	0.151	0.132	1.000
	Friendship		76	0.554	0.458	0.264	0.202	1.000
		HighTech	21	0.563	0.473	0.278	0.236	1.000
		Pharma	19	0.591	0.565	0.227	0.328	1.000
		SilSys	36	0.528	0.433	0.277	0.202	1.000

NOTE: Constraint is not rescaled.

The measures of informal social position should be controlled by other variables to isolate the significance of the positions. The next section will investigate and describe the controls needed for the hypothesis tests.

5.5 Controls

The controls are GLIs applied to the slices of each individual. The objective is to control each individual's perception for aspects of spuriousness. Applying it to the criterion graphs, offers a way to isolate the effect of actual measures such as informal social positions. There are six controls that will be explored. *First* would be the network size; since the three

[10] Also called *Burt's constraint*.

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datasets are of different sizes, the effect of size on the ability to recall the network is an obvious effect to control. *Second*, would be controls for spurious responses, by controlling for density and reciprocity. *Third*, would include controls for mental schemas, since they prove to be a powerful factor in determining the cognitive constructions observed in network perceptions (De Soto, 1960). De Soto (1960, p. 420) regards these schemas as residues of countless experiences in social interactions. Similar to decision-making heuristics, these schemas are applied in our pursuit in simplifying complex information. Researchers have since uncovered some simple schemas which influence network perceptions. Examples include gender (Neal *et al.*, 2016), experience with structural holes (Janicik and Larrick, 2005), balance (Krackhardt and Kilduff, 1999) and ego-centrism (Kumbasar *et al.*, 1994). These schemas should, therefore, be included as control variables for SNC acuity. The measures considered are transitivity, hierarchy and centralisation. A more detailed explanation of each measure is presented below. The next section, however, starts by explaining the inclusion of density as a control variable.

5.5.1 Density

Density is a control for spurious answering of the survey. Respondents can either fill in all options, thus reporting that everyone is friends with everyone, or none of the options, indicating that there are no friends. Some people might just have lower thresholds to what they consider a friend, and would nominate more relations than usual. To control for this behaviour, density is included. Network density is the fraction of reported relation relative to the maximum possible relations. Table 5.12 captures the results of the density measure for all the slices.

In Table 5.12 there are slices more than twice the mean density, for example: HighTech Advice; mean = 0.31, max = 0.66. It is, therefore, necessary to control for density, since it might be that providing a denser graph might artificially inflate the accuracy scores.

5.5.2 Reciprocity

Reciprocity is another measure to help control for spuriousness. Some people might feel inclined to always reciprocate a reported relation, such as friendship. Reciprocity is most commonly defined as the probability that the opposite counterpart of a directed edge is also included in the graph. The results are in Table 5.13.

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TABLE 5.12: *Descriptive statistics for slice density measures.*

Measure	Relation	Dataset	N	Mean	Median	SD	Min	Max
Density			152	0.149	0.113	0.128	0.000	0.660
	Advice		76	0.179	0.125	0.135	0.000	0.660
		HighTech	21	0.310	0.319	0.145	0.102	0.660
		Pharma	19	0.145	0.158	0.097	0.000	0.354
		SilSys	36	0.116	0.098	0.079	0.023	0.410
	Friendship		76	0.119	0.086	0.114	0.000	0.547
		HighTech	21	0.090	0.081	0.055	0.012	0.186
		Pharma	19	0.219	0.243	0.171	0.000	0.547
		SilSys	36	0.079	0.072	0.055	0.008	0.206

TABLE 5.13: *Descriptive statistics for slice reciprocity measures.*

Measure	Relation	Dataset	N	Mean	Median	SD	Min	Max
Reciprocity			152	0.474	0.512	0.232	0.000	1.000
	Advice		76	0.324	0.282	0.201	0.000	0.806
		HighTech	21	0.470	0.512	0.216	0.082	0.806
		Pharma	19	0.296	0.276	0.179	0.000	0.792
		SilSys	36	0.244	0.231	0.149	0.053	0.743
	Friendship		76	0.624	0.632	0.149	0.188	1.000
		HighTech	21	0.595	0.620	0.134	0.400	0.824
		Pharma	19	0.552	0.600	0.203	0.188	0.909
		SilSys	36	0.679	0.680	0.103	0.489	1.000

There are some slices that have a much higher reciprocity than average. Some slices even have a reciprocity score of 1. It is, therefore, important to control for the effect of artificially high reciprocity on acuity.

5.5.3 Transitivity

Transitivity is included as a control measure to control for the use of mental schemas. Mental schemas are aids for memory processing and encoding. For instance, transitivity is a basic inferential rule of the transitive property: if $A > B$ and $B > C$ then $A > C$. Individuals use such inference in their encoding and recall of social relations by imagining

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that if A is friends with B and B is friends with C, A would probably be friends with C. The relation between A and C is thus inferred through the transitive property, and not an actual observed relation. Good application of such inference might artificially inflate an individual's SNC acuity. This, controlling for the extent of the use of transitivity would aid in isolating actual acuity. Thus, including a measure of transitivity of a respondent's slice would be effective in controlling for the effect on their acuity. Table 5.14 reports summary statistics of the measures of transitivity on each relation over the three datasets.

TABLE 5.14: *Descriptive statistics for slice transitivity measures.*

Measure	Relation	Dataset	N	Mean	Median	SD	Min	Max
Transitivity			152	0.478	0.454	0.232	0.000	1.000
	Advice		76	0.508	0.488	0.210	0.000	1.000
		HighTech	21	0.537	0.540	0.121	0.333	0.751
		Pharma	19	0.502	0.470	0.278	0.000	1.000
		SilSys	36	0.495	0.479	0.213	0.029	1.000
	Friendship		76	0.448	0.404	0.249	0.000	1.000
		HighTech	21	0.373	0.379	0.225	0.000	1.000
		Pharma	19	0.591	0.539	0.210	0.273	1.000
		SilSys	36	0.417	0.360	0.257	0.000	1.000

The average transitivity is 0.478, with transitivity on the advice relation slightly higher than average 0.508, whereas friendship measures lower than average at 0.448. The three datasets indicate relatively similar averages on transitivity on the advice relation (SD=0.21), but there is higher deviation on the friendship relation among the datasets (SD=0.249).

5.5.4 Hierarchy

In keeping with schemas as methods to aid in recall and encoding of social relations, hierarchy is a natural schematic to order social relations. When confronted with the question of *who advises whom* or *who is friends with whom*, in producing a judgement, individuals might consider some hierarchical signals in their judgement. For instance, if John is a popular person and Jane is unknown to the respondent, the respondent would more readily indicate Jane to be friends with John, even though the respondent does not know Jane. Considering

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a third person, Jack, the respondent might judge Jack an unpopular person, and in considering the relation between Jill and Jack, one might only consider a relation from Jack to Jill, and not reciprocate the relation. This scenario might be what Everett and Krackhardt (2012) considered the *magnet* of hierarchy that models social judgements of relations. Individuals would therefore, from ignorance of dyadic relations, judge people with higher hierarchical social position as recipients of, for instance, friendship relations. In the same schematic, individuals might judge people with lower social hierarchical positions as the senders, or at least not receivers, of a social relation such as friendship.

To measure hierarchy in the informal social network, Krackhardt (1994)'s measure is applied to each slice. The summary statistics of the results are captured in Table 5.15.

TABLE 5.15: *Descriptive statistics for slice hierarchy measures.*

Measure	Relation	Dataset	N	Mean	Median	SD	Min	Max
Hierarchy			152	0.520	0.537	0.321	0.000	1.000
	Advice		76	0.602	0.698	0.361	0.000	1.000
		HighTech	21	0.282	0.095	0.364	0.000	0.976
		Pharma	19	0.663	0.763	0.320	0.000	1.000
		SilSys	36	0.774	0.857	0.228	0.000	0.989
	Friendship		76	0.438	0.432	0.251	0.000	0.938
		HighTech	21	0.495	0.514	0.245	0.000	0.857
		Pharma	19	0.447	0.536	0.327	0.000	0.938
		SilSys	36	0.398	0.394	0.209	0.000	0.798

Overall, the perceived hierarchy appears to be balanced (0.520). However, advice has higher hierarchy measures (0.602), compared to friendship (0.438). There is also high variance between the sites, especially on the advice relation (SD=0.361). Thus, there is a tendency towards a hierarchy on the advice relation, but not for friendship.

5.5.5 Centralisation

Centralisation is the combination of normal centrality measures into a graph-level indicator (Wasserman and Faust, 1994, p. 175). The more centralised the graph the more probable it is that a single actor has most centrality. Expressed otherwise, it is a measure of the variance of centrality measures in a graph. Centralisation will, therefore, equal 0 if all actors have

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the same centrality measure, and 1 if a single node completely dominates (Wasserman and Faust, 1994, p. 177).

Centralisation aids in controlling for a schema that individuals use to organise social relations. For instance, if a particular person is popular in a certain department, a centralisation schema would lead the respondent to artificially inflate their centrality, since it is an easy intuition to organise the social group around the popular individual. Consider asking X who has little personal exposure to a group, to identify the group's most knowledgeable person. X would tend to have the most popular person in the group, Z, mentally anchored as the most knowledgeable person, thus exaggerating the centrality of Z over people who are potentially more knowledgeable. Measuring the centralisation of individual slices, therefore, aid in controlling for such schemas employed by a respondent. Table 5.16 reports the summary statistics for the centralisation calculations on the slices of all respondents.

TABLE 5.16: *Descriptive statistics for slice centralisation measures.*

Measure	Relation	Dataset	N	Mean	Median	SD	Min	Max
Centralisation			152	0.119	0.102	0.105	0.000	0.549
	Advice		76	0.121	0.098	0.107	0.000	0.549
		HighTech	21	0.195	0.167	0.133	0.026	0.549
		Pharma	19	0.106	0.100	0.086	0.000	0.305
		SilSys	36	0.087	0.069	0.077	0.000	0.339
	Friendship		76	0.117	0.105	0.103	0.000	0.500
		HighTech	21	0.141	0.104	0.131	0.000	0.500
		Pharma	19	0.104	0.071	0.089	0.000	0.248
		SilSys	36	0.109	0.114	0.092	0.000	0.299

Centralisation is low, with the highest observed measurement being 0.549 on the advice relation in the HighTech dataset. The average centralisation is 0.119, with the advice relation measuring slightly higher (0.121) and friendship slightly lower (0.117).

5.6 Analysis of Variable Interactions

The above sections discussed each variable in detail while providing the summary statistics for each. The interaction between these variables should be explored further to investigate

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observable patterns and cases of collinearity between variables.

Two slices (one for advice and one for friendship) are available for each of the $N = 152$ people (who are spread across the three organisations in the study). On each of these $2 \times 152 = 304$ slices, values for 15 variables can be computed. These values are used to compute Pearson's correlation coefficient between each pair of variables.

To aid with interpretation, the variables are grouped into three groups; position measures (1-7), test controls (8-13) and acuity measures (14-15). To facilitate the report and discussion, Table 5.17 is a combination of both advice and friendship data. The report will follow this table, unless the results differ noticeably between the two relational measures, in which case Table 5.18 on Page 135 captures the correlations for advice and Table 5.19 on Page 135 for friendship.[11]

TABLE 5.17: *Correlation table containing both advice and friendship relations.*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Position														
1. Indeg														
2. Eigen	$.94^a$													
3. Betw	$.56^a$	$.51^a$												
4. ProxT	$.65^a$	$.60^a$	$.92^a$											
5. ProxS	$.25^b$	$.22^b$	$.63^a$	$.52^a$										
6. Const	$-.42^a$	$-.38^a$	$-.32^a$	$-.32^a$	$-.09$									
7. Formal	$.23^b$	$.17^c$	$.16$	$.15$	$.02$	$.00$								
Controls														
8. Size	$-.35^a$	$-.30^a$	$-.16$	$-.16$	$-.03$	$-.04$	$-.54^a$							
9. Dens	$.36^a$	$.32^a$	$.38^a$	$.39^a$	$.20^c$	$-.36^a$	$.16$	$-.41^a$						
10. Recip	$.10$	$.11$	$.25^b$	$.25^b$	$.08$	$.27^b$	$.14$	$-.03$	$.19^c$					
11. Trans	$.18^c$	$.19^c$	$.25^b$	$.25^b$	$.16$	$-.21^c$	$.15$	$-.18^c$	$.53^a$	$.16$				
12. Hier	$-.15$	$-.13$	$-.22^b$	$-.25^b$	$-.07$	$.03$	$-.14$	$.17^c$	$-.61^a$	$-.72^a$	$-.34^a$			
13. Centz	$.11$	$.06$	$.10$	$.08$	$.04$	$-.22^c$	$.13$	$-.17^c$	$.31^a$	$.19^c$	$.04$	$-.54^a$		
Acuity														
14. Interp	$.28^a$	$.29^a$	$.22^b$	$.18^c$	$.19^c$	$-.33^a$	$-.04$	$.21^c$	$-.12$	$-.06$	$.03$	$.08$	$.08$	
15. Struct	$.31^a$	$.32^a$	$.26^b$	$.22^b$	$.19^c$	$-.19^c$	$.00$	$.04$	$.02$	$.16$	$.01$	$-.12$	$.21^c$	$.66^a$

NOTES: $a = p < .001$; $b = p < .01$; $c = p < .05$

[11] To aid with space, the variables are presented with shortened labels. They correspond as follows: Indeg = indegree centrality, Eigen = eigenvector centrality, Betw = betweenness centrality, ProxT = proximal target betweenness centrality, ProxS = proximal source betweenness centrality, Const = constraint, Formal = formal social position, Size = network size, Dens = network density, Recip = reciprocity, Trans = transitivity, Hier = Krackhardt's hierarchy, Centz = centralisation, Interp = interpersonal SNC acuity, Struct = structural SNC acuity.

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TABLE 5.18: *Correlation table for only the advice relation.*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Position														
1. Indeg														
2. Eigen	$.95^a$													
3. Betw	$.45^a$	$.42^a$												
4. ProxT	$.57^a$	$.54^a$	$.93^a$											
5. ProxS	$.09$	$.08$	$.56^a$	$.46^a$										
6. Const	$-.28^c$	$-.25^c$	$-.22$	$-.22$	$.32^b$									
7. Formal	$.48^a$	$.50^a$	$.22$	$.24^c$	$-.01$	$-.26^c$								
Controls														
8. Size	$-.36^b$	$-.30^c$	$-.14$	$-.15$	$.02$	$-.06$	$-.54^a$							
9. Dens	$.17$	$.14$	$.29^c$	$.29^c$	$.11$	$-.26^c$	$.40^a$	$-.44^a$						
10. Recip	$.18$	$.16$	$.47^a$	$.45^a$	$.22$	$-.27^c$	$.40^a$	$-.34^b$	$.85^a$					
11. Trans	$.11$	$.14$	$.27^c$	$.28^c$	$.16$	$-.31^b$	$.17$	$-.12$	$.56^a$	$.47^a$				
12. Hier	$-.05$	$-.03$	$-.27^c$	$-.27^c$	$-.07$	$.23$	$-.34^b$	$.41^a$	$-.89^a$	$-.88^a$	$-.48^a$			
13. Centz	$-.06$	$-.05$	$.00$	$-.01$	$-.08$	$-.12$	$.25^c$	$-.29^c$	$.36^b$	$.44^a$	$.17$	$-.62^a$		
Acuity														
14. Interp	$.18$	$.21$	$.25^c$	$.25^c$	$.18$	$-.25^c$	$-.13$	$.55^a$	$-.26^c$	$-.15$	$.07$	$.29^c$	$-.21$	
15. Struct	$.36^b$	$.36^b$	$.39^a$	$.40^a$	$.21$	$-.21$	$-.06$	$.16$	$.12$	$.14$	$.24^c$	$-.07$	$-.01$	$.61^a$

NOTES: $a = p < .001$; $b = p < .01$; $c = p < .05$

TABLE 5.19: *Correlation table for only the friendship relation.*

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Position														
1. Indeg														
2. Eigen	$.92^a$													
3. Betw	$.74^a$	$.65^a$												
4. ProxT	$.77^a$	$.69^a$	$.90^a$											
5. ProxS	$.72^a$	$.61^a$	$.91^a$	$.77^a$										
6. Const	$-.70^a$	$-.63^a$	$-.61^a$	$-.57^a$	$-.60^a$									
7. Formal	$-.02$	$-.16$	$.08$	$.03$	$.10$	$.14$								
Controls														
8. Size	$-.35^b$	$-.30^c$	$-.19$	$-.19$	$-.19$	$-.05$	$-.54^a$							
9. Dens	$.62^a$	$.57^a$	$.55^a$	$.58^a$	$.46^a$	$-.32^b$	$-.11$	$-.39^a$						
10. Recip	$.02$	$.08$	$.05$	$.12$	$.00$	$-.10$	$-.10$	$.36^b$	$-.09$					
11. Trans	$.26^c$	$.25^c$	$.26^c$	$.24^c$	$.21$	$-.07$	$.14$	$-.23$	$.49^a$	$.26^c$				
12. Hier	$-.29^c$	$-.27^c$	$-.15$	$-.24^c$	$-.17$	$.26^c$	$.12$	$-.14$	$-.42^a$	$-.53^a$	$-.35^b$			
13. Centz	$.28^c$	$.19$	$.24^c$	$.21$	$.36^b$	$-.34^b$	$.01$	$-.04$	$.26^c$	$.03$	$-.07$	$-.49^a$		
Acuity														
14. Interp	$.38^b$	$.37^b$	$.19$	$.11$	$.26^c$	$-.42^a$	$.04$	$-.07$	$-.04$	$.10$	$-.02$	$-.19$	$.32^b$	
15. Struct	$.26^c$	$.29^c$	$.13$	$.04$	$.23$	$-.36^b$	$.05$	$-.07$	$-.03$	$.11$	$-.12$	$-.14$	$.40^a$	$.71^a$

NOTES: $a = p < .001$; $b = p < .01$; $c = p < .05$

5.6.1 Position Measures

As expected, there is a strong correlation among the centrality measures (see Valente *et al.*, 2008). Two pairs of highly correlated measures are indegree centrality and eigenvector centrality (r = .94, $p \leq$.001), as well as betweenness centrality and proximal target centrality (r = .92, $p \leq$ .001). The first relation is to be expected, since eigenvector centrality is conceptually similar to indegree centrality (see Everett and Borgatti, 2005). The second pair

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is because proximal target centrality is a specialised measure of betweenness centrality (see Brandes, 2008). The interaction between constraint and the centrality measures is also as expected. Note that, the higher the constraint, the less access to structural holes, thus a negative relation between constraint, and the centrality measures. Among the significant correlations,[12] the relationship is weakest with the medial measures—betweenness and proximal target (r = -.32, $p \leq .001$)[13]— and stronger negative with the radial measures—indegree (r = -.42, $p \leq .001$) and eigenvector (r = -.38, $p \leq .001$). Lastly, the interaction between formal position and the other position variables is only evident for the radial measures indegree and eigenvector in Table 5.17. As mentioned in Chapter 4, the second hypothesis (H2a) is that formal position should lead to social position, specifically on the advice relation. Considering the advice relation in isolation, in Table 5.18 the significant positive relation remains (r = .48, $p \leq .001$), but this relation disappears when considering the friendship relation in Table 5.19, where there is no sign of a relation between formal position and social positions: indegree (r = -.16, $p < .05$) and eigenvector (r = -.02, $p < .05$). There is, therefore, further evidence that the argument is supported, and should be explored further.

5.6.2 Position measures and controls

Consider the interaction between position measures (1-7) and controls (8-13). Network size has a significant negative impact only with the radial measures of centrality—indegree (r = -.35, $p < .001$) and eigenvector (r = -.30, $p < .001$)—as well as formal position (r = -.54, $p < .001$). The pattern is the same for both advice and friendship. The other control measures have different interactions with the position measures for the two relational dimensions, and will, therefore, be reported separately.

5.6.2.1 Advice

On the advice relation, density has a significant relation with the medial centrality measures—betweenness and proximal target (r = .29, $p < .05$)—constraint (r = -.26, $p < .05$), and formal position (r = .40, $p < .001$). This pattern is repeated with reciprocity (which has a stronger interaction overall), transitivity and hierarchy. The only exceptions are that transitivity does not have a significant relation with formal position, and hierarchy has an inverse

[12]Thus ignoring the interaction between constraint and proximal source.
[13]The correlation is the same for both measures.

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relation with the positional measures. The perception of network centralisation only has a significant interaction with formal position, indicating a positive relation (r = .25, $p < .05$).

5.6.2.2 Friendship

Considering the friendship relation, density has a significant interaction with all position variables except formal position. The strongest interaction is with indegree (r = .62, $p < .001$), followed by proximal target (r = .58, $p < .001$), eigenvector (r = .57, $p < .001$), betweenness (r = .55, $p < .001$), proximal source (r = .46, $p < .001$) and a negative relation with constraint (r = -.32, $p < .01$). Transitivity has a similar interaction with all positions except formal position. Except for betweenness, hierarchy has a significant negative correlation with all centrality measures and a positive relation with constraint (r = .26, $p < .05$). The strongest interaction for centralisation is with proximal source (r = .36, $p < .01$) followed by a significant negative correlation with constraint (r = -.34, $p < .01$), then indegree (r = .28, $p < .05$) and betweenness (r = .24, $p < .05$).

5.6.3 Acuity, Position and Controls

The interaction between SNC acuity (14-15), controls (8-13) and position (1-7) differs enough between friendship and advice to report separately.

5.6.3.1 Advice

Starting with advice in Table 5.18, interpersonal acuity only significantly correlates with medial measures of centrality (r = .25, $p \leq .05$) and constraint (r = -.25, $p \leq .05$), whereas structural acuity significantly correlates with all positions except constraint. The strongest interaction between structural acuity and position is on the medial measures of position; proximal target (r = .40, $p \leq .001$), closely followed by betweenness (r = -.39, $p \leq .01$). Important to note here is that there is no relation between any of the two acuity measures and formal position, concordant with H1a.

The only interaction between the acuity measures, and the test controls is between interpersonal acuity and size (r = .55, $p \leq .001$), density (r = -.26, $p < .05$) and hierarchy (r = .29, $p < .05$). Structural acuity only correlates with transitivity (r = .24, $p \leq .05$).

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5.6.3.2 Friendship

Considering the same interactions on the friendship relation, different patterns emerge. The nuance between structural and interpersonal acuity is not as evident, since both measures are mirrored in their interactions with the other variables. Looking at acuity and position measures, both measures follow the same interaction patters, with interpersonal acuity having a slightly stronger interaction overall. The strongest interaction is observed between constraint and interpersonal acuity (r = -.42, $p \leq .001$). Considering the control measures, only centralisation is significantly correlated with the two acuity measures: interpersonal (r = .32, $p \leq .01$) and structural (r = .40, $p \leq .001$). H1a is again confirmed on the friendship relation, since there is no correlation between formal position and either acuity measure. Lastly, evidently the two measures of proximal betweenness centrality—source and target—interact as expected. Indicated previously, proximal target betweenness is a more appropriate measure for advice, whereas proximal source should be used for the friendship relation. This is confirmed, since proximal target only significantly interacts with acuity measures on advice, whereas proximal source is the only medial measure interacting with acuity measures (r = .26, $p < .05$).

5.6.4 Conclusion

Relating to the proposed argument, there are three key takeaways from the correlations. *First*, H1a is confirmed for both the advice and friendship relations, as well as the overall effect in Table 5.17. The hypotheses can, therefore, be explored further, since it confirms the finding from previous literature, but contradicts the findings from Casciaro (1998), who found a negative relation. The *second* important point to conclude from the correlations is that there are significant interactions between the control variables and the independent and dependent variables to warrant their inclusion into a regression test. *Third*, there is clear interaction between the independent and dependent variables that warrants further investigation to support the proposed argument.

The following offers a general summary of the above:

- Advice
  - The level of hierarchy and transitivity in the network moderates radial social positions.

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  - Reciprocity uniquely controls for indegree positions. The more reciprocated a network, the higher the chances of having high indegree.
  - Only centralisation controls for constraint. The more centralised a network the less structural holes *available* i.e., in a star formation network there is only one position and many structural holes.
  - Higher Formal position leads to higher radial central positions, gate-keeping and less constraint.
  - Structural acuity leads to all positions except constraint. It is strongest for the most agency viable positions: medial.
  - Interpersonal acuity leads to medial positions and less constraint.
  - Only interpersonal acuity correlates with size.
- Friendship
  - Density moderates radial social positions . The denser the higher the chance of high indegree.
  - Centralisation and reciprocity control for indegree centrality. The more centralised the network, the more central actors available. Reciprocity artificially inflates indegree.
  - Formal position has no effect on social position.
  - Size negatively impacts on radial social positions.
  - Acuity (both measures) relates to radial positions, and not medial positions and less constraint. People with affective acuity will be befriended more, and will interact with a wider group, thus less constraint.

5.7 Regression Preparation

At this point it is necessary to review the central argument. It is the main proposition for this thesis that SNC accuracy leads to favourable network positions. Based on prior literature the relationship between SNC acuity and social position does exists, but previous research considered the relationship in the opposite direction: social position leads to acuity. It was then argued that if this was the case, the same should hold for the formal variant of social position found in the organisational hierarchy, especially considering the exposure theory as the forwarded explanation.

The same literature either found no relationship between formal position and acuity,

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or found a negative relation, indicating that more authoritative individuals have less accurate network perceptions. The reason offered for the difference is that these individuals do not need SNC acuity, since they are already occupying advantageous positions in the organisation. The problem with this argument is that the mechanism forwarded for acuity (advantageous position) relies on the individual receiving benefit (acuity) from the network structure, without having to actively seek it. Thus, motivation is not part of the mechanism. Moreover, it might be that individuals, once in a favourable position, are ignoring social dynamics, thus a negative interaction between acuity and certain social positions should be expected that is not found in prior literature.

If H1a, H2b and H3b are supported, it is proposed, the direction of prediction should be reconsidered. This is where: H1a posits that there is no significant correlation between formal position and social network acuity; H2b proposes formal position as a significant positive predictor for informal social position; and, H3b states that SNC acuity is a significant positive predictor of informal social position.

The previous section has already supported H1a using Pearson correlation. There is also evidence of H2b and H3b. There are however confounding variables that need to be controlled for, while certain predictors and response variables indicate significant multicollinearity. To perform a multivariate linear regression for inference, two steps are required. Firstly, a PCA is used to perform variable reduction to deal with the multicollinearity problem. Secondly, the assumptions of a linear regression model is addressed, and a specific application is proposed.

5.7.1 Variable Reduction

It was evident from Section 5.6 that there are collinearity amongst both response and predictor variables. When performing a multiple linear regression it is prudent to check and remedy both collinearity and multicollinearity (James, Witten, Hastie and Tibshirani, 2013). The regression tables are only capable of identifying collinearity. To observe multicollinearity among the response and predictors, it is best to perform a variance inflation factor (VIF) analysis (James *et al.*, 2013, p. 101). The next sections will evaluate each class of variable in turn.

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5.7.1.1 Response Variables

Recall that the response variables are indegree, eigenvector, betweenness, proximal target, proximal source, and constraint. In Section 5.6 there is high correlations between measures of social positions, especially within the radial (indegree and eigenvector) and medial (betweenness and proximal target/source) groups of measures. It would, therefore, make sense to combine these response variables into the two classes where they highly correlate. A PCA is a reasonable method to produce a compound variable by taking the eigenvectors of the principal components (Song, Lin, Ward and Fine, 2013).

To create a compound variable for each category, the response variables are analysed using PCA. indegree and eigenvector are used as constituting a radial measure of social position, whereas the betweenness and proximal target and source measures would combine to produce a medial measure of social position. This process is done on the whole dataset, and repeated separately for both the advice and friendship relations. The first principal component is then extracted as the compound variable, and the eigenvectors can be used in the regression analysis. Table 5.20 displays the standard deviation and proportion of variance explained by the first principal component of each combination of radial and medial response variables.

TABLE 5.20: *First component of radial and medial response variables.*

	Advice		Friendship		All Relations	
	Radial	Medial	Radial	Medial	Radial	Medial
Standard deviation	1.40	1.39	1.39	1.38	1.39	1.38
Proportion of Variance	0.98	0.96	0.96	0.96	0.97	0.96

The first principal component for each composite explains at least 96% of the variance in the data and would, therefore, be enough in substituting the individual measures. This process thus leaves three response variables: radial, medial and constraint. Note that proximal target is used with betweenness to create the medial measure only on the advice relation, while the proximal source is used on the friendship relation. The rationale for this is explained earlier in Section 5.4.1.4, while in the correlation tables in Table 5.18 and Table 5.19 highlight that proximal source only significantly correlates with the predictors on the friendship relation, and proximal target only on the advice relation. Table 5.21 displays

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the factor loadings for the PCA for all response variables, while combining the advice and friendship relations.

TABLE 5.21: *Factor loadings for all response variables.*

	PC1	PC2	PC3	PC4	PC5	PC6
Indegree	-0.4544	0.3568	-0.3079	0.1903	-0.1810	**0.7088**
Eigenvector	-0.4354	0.3851	-0.3701	0.2397	0.2657	**-0.6302**
Betweenness	-0.4633	-0.3302	0.1003	-0.4011	**0.6836**	0.1950
Proximal Target	-0.4781	-0.2011	-0.0217	-0.5051	**-0.6449**	-0.2438
Proximal Source	-0.2997	**-0.6359**	0.1180	**0.6915**	-0.1119	-0.0350
Constraint	0.2662	-0.4130	**-0.8624**	-0.1102	0.0311	0.0414
Standard deviation	1.8879	1.0774	0.8554	0.6457	0.2598	0.2425
Proportion of Variance	0.5940	0.1935	0.1220	0.0695	0.0112	0.0098
Cumulative Proportion	0.5940	0.7875	0.9095	0.9789	0.9902	1.0000

Note: Loadings higher than 0.6 are in bold.

Thus, proximal source and constraint will be retained as separate response variables to consider in the regression models.

5.7.1.2 Predictor Variables

The predictor variables can be considered in three groupings—control, acuity measures and formal position. The control grouping consists of network size, density, reciprocity, transitivity, hierarchy, and centralisation. While the acuity grouping contains interpersonal and structural SNC accuracy measures.

To check for multicollinearity related to the response variable, James *et al.* (2013) suggests using the VIF method. When considering all predictors Table 5.22 indicates, in bold, the predictors that show collinearity (VIF > 5). Evidently, three control variables have collinearity, specifically on the advice relation: density, reciprocity and hierarchy. The two accuracy measures also have collinearity as is expected, and since they are key variables they can be included independently in linear models. Nevertheless, it might be prudent to create a general *acuity* measure. The collinearity is not high enough to warrant removal of variables as proposed by James *et al.* (2013, p. 102) suggests that a compound variable approach, as with the response variables, would be more suited.

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TABLE 5.22: *Variable inflation factor results for all predictors on the radial and medial response variables.*

Relation	All	Advice	Friendship
Size	1.85	2.39	2.60
Trans	1.50	1.57	1.83
Centralisation	1.84	2.56	1.91
Formal	1.52	1.83	1.94
Interpersonal	2.09	2.97	2.16
Structural	2.04	2.02	2.33
Dens	2.85	**9.07**	2.87
Reciprocity	3.30	**5.45**	2.07
Hierarchy	**6.09**	**14.29**	3.04

A composite variable of density, reciprocity, and hierarchy would, therefore, benefit the model. The first component of these three variables explain 92% of variance, with a standard deviation of 1.66. After replacing these variables with the loadings of the first component, another VIF produces no variables above the threshold of 5.

This process thus produces four predictor variables; network size, spurious controls, perceived centralisation, perceived transitivity, SNC acuity and formal position. With the variables cleaned prepared for regression, the next section will tend to the issue of the assumptions of regression procedures, and the particular considerations in this context.

5.7.2 Multiple Regression Quadratic Assignment

Successfully applying regression analysis, like with most classic statistical tests, depends on certain critical assumptions. There are obvious assumptions such as the assumption of a linear relationship. However, two assumptions are of particular importance here. *First*, an ordinary least squares (OLS) regression assumes the response variable is from a population that follows a Gaussian distribution. *Second*, a regression model assumes that all observations are independent. Social network data routinely violates both assumptions. This is partially because of the well publicised long-tail distributions often found in SNA data (Barabási and Albert, 1999; Krackhardt, 1987*b*; Newman, Barabási and Watts, 2006). The most notorious of such distributions is the degree distribution of social networks that hardly ever produces a normal distribution (Barabási and Albert, 1999). Moreover, the observations are not independent (see Krackhardt, 1987*b*).

There are a few strategies available to account for the two violations. The skew distribution can be transformed by applying a log transformation on the data, or by more

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sophisticated methods such as the Tukey ladder of power transformation procedure. The independence of the observations can be somewhat remedied by the inclusion of the three datasets that offer cross-validation of any potential autocorrelation. However, the transformation of the response variables offered mixed results, hardly satisfying the Shapiro-Wilks test for normality after transformations. Moreover, there are multiple linear regression implementations that counter the issue of independent observations that would make such an exercise redundant.

The most applicable solution that would resolve the issues of both violations is to use resampling statistics, or more specifically, permutation tests. Instead of testing against a theoretical distribution, a permutation test creates an empirical distribution from permutations of the observed data (Kabacoff, 2015, p. 281). This resolves the issue with both the lack of normal distribution of response variable and independence of observations. From within SNA literature, there the multiple regression quadratic assignment procedure (MRQAP). The bivariate version of the method, the quadratic assignment procedure (QAP), was introduced as a non-parametric test for the significance of an association between two matrices with complex dependencies. This was extended to a multi-variate regression and introduced to the SNA context by Krackhardt (1987*b*). Subsequent extensions of the method have been developed, the most recent of which by Dekker, Krackhardt and Snijders (2007), who proposed a permutation of the residuals, rather than the raw matrices, to account for method biases.

The intuition behind the method is to take the dependent variable in the form of a matrix, and permute the rows and columns of the matrix. While preserving the internal dependencies between the observations in the dependent variable, the dependencies between the dependent and independent variables are effectively removed. The permutation therefore preserves the relation between observations, such as *friends with* or *likes*, and although the predictors are expected to have a correlation with these observations, they are not expected for the permuted versions of the response variable. Thus, if there is a relation found between the predictors and permuted response variable, the results are possibly spurious (Cranmer, Ohio, Leifeld, Eth, Mcclurg and Rolfe, 2017).

The method requires that the data is presented in a square matrix format. It is possible to convert non-matrix variables in two ways. *First*, the vector can simply be duplicated across the columns of the matrix. This preserves the measurement of each observation relative to all other observations. The *second* approach is to create a distance matrix from the

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vector. This is achieved in multiple ways, and depends on the context. The simplest method would be to deduct j from i for each cell, where i is the row, and j the column. This effectively calculates the distance between observations, and preserves the underlying structure of the observations, if any. Table 5.23 illustrates the two methods, where Table 5.23b illustrates the result of the duplication method,and Table 5.23c is the result of the distance calculation.

TABLE 5.23: *Attribute to matrix procedures.*

$$\begin{array}{cc} & Var \\ \begin{matrix} i_1 \\ i_2 \\ i_3 \\ i_4 \\ i_5 \end{matrix} & \begin{bmatrix} 3 \\ 5 \\ 2 \\ 10 \\ 4 \end{bmatrix} \end{array}$$

(A) *Attribute*

$$\begin{array}{cc} & \begin{matrix} j_1 & j_2 & j_3 & j_4 & j_5 \end{matrix} \\ \begin{matrix} \cdots \\ \cdots \\ \cdots \\ \cdots \\ \cdots \end{matrix} & \begin{bmatrix} 3 & 3 & 3 & 3 & 3 \\ 5 & 5 & 5 & 5 & 5 \\ 2 & 2 & 2 & 2 & 2 \\ 10 & 10 & 10 & 10 & 10 \\ 4 & 4 & 4 & 4 & 4 \end{bmatrix} \end{array}$$

(B) *Column-wise duplication*

$$\begin{array}{cc} & \begin{matrix} j_1 & j_2 & j_3 & j_4 & j_5 \end{matrix} \\ \begin{matrix} \cdots \\ \cdots \\ \cdots \\ \cdots \\ \cdots \end{matrix} & \begin{bmatrix} 0 & -2 & 1 & -7 & -1 \\ 2 & 0 & 3 & -5 & 1 \\ -1 & -3 & 0 & -8 & -2 \\ 7 & 5 & 8 & 0 & 6 \\ 1 & -1 & 2 & -6 & 0 \end{bmatrix} \end{array}$$

(C) *Distance Matrix*

5.8 Regression Results

The objective of performing a multiple linear regression is best captured by the following questions adapted from James *et al.* (2013, p. 75).

1. Does the proposed linear model significantly predict the response variables?
2. Do any of the proposed predictors, apart from the controls, contribute to an informative and significant improvement in predicting the response variables?
3. Does the acuity predictor help to explain all social positions, or only certain ones?
4. How well does formal position predict informal position on each relation?

5.8.1 All Relations

The first step is to understand how well the two key predictors—acuity and formal position—are regressed on informal social positions, while disregarding the differences in friendship

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TABLE 5.24: *MRQAP results for both advice and friendship relations.*

	Radial	Medial	Constraint
Controls			
Size	-0.36^{***}	-0.09	-0.06
Spurious	0.16	0.28^{**}	0.18
Centralisation	-0.11	-0.10	-0.25^{**}
Transitivity	0.06	0.12	-0.28^{**}
Key Predictors			
Acuity	0.40^{***}	0.28^{***}	-0.23^{**}
Formal	-0.00	0.03	0.00
Adj. R^2	0.29	0.20	0.18
F-statistic	1353.10	821.15	714.17

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Note: Number of Observations = 142

Beta coefficients are standardised.

and advice relations. This offers insights of how well acuity performs as a general predictor of social position, regardless of the network type. Table 5.24 records the MRQAP results.[14]

The model better explains radial positions in the informal social network (R^2= 0.29), with medial network positions (R^2= 0.20) and constraint (R^2= 0.18) indicating lower explained variance. Among the control variables, size only significantly relates to radial measures of social position (β = -0.36, $p < 0.001$), whereas the composed control variable of spuriousness is only significantly related to medial network positions (β = 0.28, $p < 0.001$). Centralisation and transitivity are both only significantly related to the constraint measure of social position (centralisation: β = -0.25, $p < 0.01$; transitivity: β = -0.28, $p < 0.01$).

Given the controls, acuity is consistently a significant positive predictor of social positions (radial: β = 0.40, $p < 0.001$; medial: β = 0.28, $p < 0.001$), except with constraint where it is a significant negative predictor (β = -0.23, $p < 0.01$). Formal position is not a significant predictor of any network positions when ignoring the relation type.

Collapsing advice and friendship relations is helpful in determining the overall predictive power of SNC acuity on network positions in general. However, conflating the two

[14] All regressions are based on 1000 permutations, using Dekker's *semi-partialling plus* procedure (Dekker *et al.*, 2007).

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TABLE 5.25: *MRQAP results on advice relation.*

	Radial	Medial	Constraint
Controls			
Size	-0.38^{**}	-0.17	-0.27
Spurious	0.07	-0.40^{*}	0.16
Centralisation	-0.17	-0.22	-0.03
Transitivity	-0.01	-0.00	-0.17
Key Predictors			
Acuity	0.48^{***}	0.45^{**}	-0.17
Formal	0.41^{**}	0.08	-0.33^{*}
Adj. R^2	0.48	0.35	0.24
F-statistic	762.84	453.89	265.94

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Note: Number of observations = 71

Beta coefficients are standardised.

relational types is a naïve approach. The following sections offer a more in-depth report on the results by isolating advice and friendship relations in the MRQAP analysis.

5.8.2 Advice Relation

The same MRQAP method is applied to the data, while only considering the advice relations reported by respondents. The results are reported in Table 5.25. All the variables as in the previous section, except for the medial response variable, which is a PCA composition omitting proximal source betweenness including only betweenness and proximal target betweenness.

The linear model explains as high as 48% of variance in radial measures of network position. This can be attributed to high beta coefficients for both acuity (β = 0.48, p $<$ 0.001) and formal position (β = 0.41, p $<$ 0.01). The model is also able to explain 35% of variance of the medial social network position, with only acuity as a significant predictor (β = 0.45, p $<$ 0.01). The linear model explained the least variance for constraint (R^2=0.24), with only formal position being a significant negative predictor of a constrained informal position (β = -0.33, p $<$ 0.05).

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TABLE 5.26: *MRQAP results on friendship relation.*

	Radial	Medial	Constraint
Controls			
Size	-0.52^{***}	-0.15	-0.01
Spurious	-0.31^{*}	-0.09	0.14
Centralisation	-0.01	0.23	-0.15
Transitivity	0.07	0.19	-0.06
Key Predictors			
Acuity	0.30^{**}	0.12	-0.36^{**}
Formal	-0.36^{**}	-0.01	0.14
Adj. R^2	0.45	0.20	0.27
F-statistic	669.64	202.31	300.17

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

Note: Number of observations = 71

Beta coefficients are standardised.

The significant result of formal position as a predictor is expected, since individuals with higher formal positions might be approached more for advice than individuals lower in the formal hierarchy. Moreover, formal position is unable to predict medial positions in the social network that suggest that the formal position is not necessarily a strategic positioning relative to sources (medial positioning), but rather a source of advice itself (radial positioning). This is an important finding, since the stated hypotheses, H2b is supported, while rejecting both H2a and H2c. Moreover, H3b is further supported, specifically on the advice relation.

5.8.3 Friendship

Table 5.25 reports the results when considering the same linear model as above, but on the friendship relation. Note that in this case, the medial response variable is a composition of betweenness and proximal source betweenness.

Radial measures of social position on the friendship relation—i.e. being popular or being friends with popular people—is significantly predicted by the proposed model (R^2= 0.45, F= 669.64, p <0.001), with network size being the strongest predictor (β = -.52,

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$p < .001$), followed by formal position (β = -.36, $p < .01$), and SNC acuity (β = .30, $p < .01$). None of the predictors were able to significantly predict medial measures of network positions, whereas formal position was the only significant predictor of constrained network positions (β = -.36, $p < .01$).

Notice that formal position is a negative predictor of radial position, suggesting that the higher an individual is placed in the organisational hierarchy, the less they are perceived as a friend.

Relating to the stated hypothesis, the results of the regression again supports H3b by showing that social acuity is a significant predictor of social network position. A significant negative relation was found for formal position as a predictor of social position that supports H3c offering conditional support for the overall argument.

5.9 Conclusion

Relating back to the questions that informed the regression analysis, there are some key insights from the results.

First, the proposed linear model significantly predicts informal social positions in both the advice and friendship networks, as well as when they are combined. The model was able to predict as high as 48% variance, and the lowest R^2 is reported for constraint, when both relations are grouped. When only considering either advice or friendship relations, the lowest explained variance by the model is again 20% but this time for medial social positions on the friendship relation. Radial positions are overall better explained by the model, with a reported R^2 of 0.48 for advice, 0.45 for friendship and 0.29 for both, while the model's performance on medial positions weaker with an R^2 of 0.35 for advice, 0.20 for friendship and 0.20 for both, and constraint an R^2 of 0.24 for advice, 0.27 for friendship and 0.18 for both.

Second, while controlling for network size and spurious responses, acuity is a significant predictor in all cases of predicting social positions, for advice and friendship networks, as well as when both relations are combined. In predicting radial and medial positions, acuity tends to have the highest standardised coefficients, except on the friendship relation, where formal position has a stronger negative prediction. However, on predicting a constrained social position in the friendship network, acuity outperforms formal position, whereas formal position is the better predictor in advice and when considering both relations. Formal

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position not a significant predictor of medial positions, only for radial positions and constraint.

Third, acuity is not a significant predictor of all informal network positions in all relations. When ignoring social relation, acuity is the only key predictor. However, acuity is unable to significantly contribute in predicting a constrained social position in the advice network, while it can in the friendship network, where it fails to significantly predict medial social positions.

Lastly, formal position is a significant predictor of radial social positions in both the advice and friendship network, but is only significant on predicting constrained advice positions.

Related to the stated hypothesis in Section 3.7.1, the correlation coefficients supported H1a that states that there is no relation between acuity measures and formal position. Evidence for further exploration of hypothesis two and three is found in the correlation tables, showing various interactions between social position and accuracy measures. However, the presence of conflating variables that correlate significantly with measures of social position meant that a multivariate approach is warranted to control for particular variables to measure the effect of the key predictors on social position. Through a process of data preparation and evaluation of the linear regression model assumptions, both predictors and response variables are considered for composition to preserve a cleaner model. The variables are prepared for a MRQAP method that entails creating a distance matrix of all variables to control for the autocorrelation. The MRQAP method produced results that provide further evidence for hypotheses two and three. Specifically, H2b and H2c are supported, which states that formal position is a significant predictor of informal social positions, where H2b hypothesises a positive relation, and H2c a negative relation. H2b is supported only on the advice relation, whereas H2c is supported only on the friendship relation. H3b is supported in all cases of radial social positions, but not for medial positions in the friendship network, or constrained advice positions.

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PART III

DISCUSSION & CONCLUSION

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CHAPTER 6

DISCUSSION

When asked to provide information about relationships in their social network, individuals are repeatedly inaccurate (Killworth and Bernard, 1976). This is a surprising observation, considering the importance for individuals to understand and navigate social relations (Dunbar, 1998). However, some individuals are indeed capable of achieving an accurate perception, prompting questions about why some are more accurate than others (Krackhardt, 1987*a*). Investigating the causes for social network acuity consistently surfaces two key variables: social network position and personality. The focus is mostly on the proposition that network position is the key antecedent to SNC acuity. Although not formalised, two theories attempt to account for why network position relates to acuity. The first is *exposure* theory, and the second, *networking* theory. To conclude, the two theories are formally outlined and contrasted, and are used to interpret the empirical findings from Chapter 5. The implications from the conclusions are then interpreted relative to reviewed literature from Chapter 3 and Chapter 2.

6.1 Introduction

As a key human cognitive trait, SNC acuity becomes increasingly important in a society with expanding individual social networks—due to new tools such as social media platforms—and widely accessible communication platforms through mobile phones (Wellman, 2000). Prior to the advent of internet and social media, emigration caused an individual to sever almost all of their existing social ties, and subsequently establish a completely new network at their destination. With the aid of modern communication platforms, maintaining distant relations becomes commonplace. The platforms additionally enable previously severed relations to be re-established.

At first, this ability could be regarded as a major leap in social capital in society, especially considering Metcalfe's law, where the value of the network increases with its size. However, there are rising concerns around individual cognitive limits, and the effect it has

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in modern society with cited issues such as fake news and echo chambers (Del Vicario *et al.*, 2016; Ferguson, 2017; Sunstein, 2017).

The ability to accurately encode and navigate personal social networks plays a key role in this new context. Many issues of digital misinformation, and phenomena such as *echo chambers* might be artefacts of poor social network acuity, or a general lack of ability to understand one's network structure.[1] Social acuity is, therefore, a key trait to investigate. Yet, previous research regard accuracy as a consequence of an individual's network position, rather than regarding accuracy itself as a key contributing factor of informal network position. The implication on the local analogue level of social networks, such as in organisations, could inform broader implications for digital social networks.

The following section outlines two theories: *networking* and *exposure*. Exposure theory is forwarded as the theoretical formalisation within current literature to explain empirical observations around SNC acuity. Networking theory is subsequently formulated and proposed as a more congruent approach to explaining the empirical findings of a reversed causation between SNC acuity and informal social position. By highlighting a key logical shortcoming in the use of exposure theory in explaining empirical findings, the preference of networking theory over exposure theory is proposed. After outlining the two theories, the empirical results from the previous chapter are subsequently reviewed in relation to the proposed theories. This chapter further investigates the implication of the findings for an increasingly wider context.

6.2 Networking Versus Exposure

Networking or exposure theory are collections of assumptions about how individuals encode, recall and utilise their social networks. Networking theory offers a cognitive-behavioural agenda to understand how individuals perform these functions, while exposure theory offers a structural view of the same processes. It is prudent to draw parallels with these two distinctions and the *agency-structure* debate that has been a key part of theoretical conversations throughout the history of SNA (Borgatti, Brass and Halgin, 2014). The following sections investigate the networking and exposure theories, while keeping notes on the structure-agency debate.

[1] Echo chambers are homogenous and polarised communities in a social network (Del Vicario *et al.*, 2016). The name comes from the effect of shouting in a chamber, merely echoing the same exclamation back.

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6.2.1 Exposure Theory

Exposure theory is developed from constructional theory, proposed by Carley (1990), and the processes outlined by Pattison (1994). It is introduced by Casciaro (1998) as a theoretical framework to investigate SNC acuity. Exposure theory posits that exposure to more information about the network structure would enable an individual to accurately recall the network. Exposure can be through direct exposure of information flowing in the network, or it can be exposure to certain patterns of direct interaction, such as structural holes (Janicik and Larrick, 2005). To formalise exposure theory within this context, three mechanisms are proposed here. Each mechanism will be explored in more detail in the following sections.

6.2.1.1 Reach

Reach is the extent of an individual's access to their network. This access could be from actual connections made, such as friendships or acquaintances, or it can be purely observational without any bilateral contact. An individual who only has exposure to a small subset of alters in a network would be less accurate than an individual with wider exposure. Consider an individual who must interact with a wider subset of individuals in the organisation due to the nature of their job. An HR manager, for instance, has a wide exposure to employees in an organisation. Such an individual has a higher chance of developing a wider perception, or set of connections in the network.

Other key aspects of reach to consider is the influence of physical space and routines. Compare the reach of individuals in an office environment where there are only closed-off offices and one where it is open-plan. The open office would offer a much wider reach to individuals. Thus, the individuals in an open-plan office would be more accurate in judging relations—even if they were to resort to guessing—since they have exposure to frequent cubicle visits and encounters between other people. The information of cubicle encounters of others is, however, not available to those in a closed office environment, or at the least, it is much more restricted. Additionally, consider the comparison between single and multi-site work environments. Consultants working at a client's office have more reach in the networks at the client than their own office. Thus, they would have a tougher time relaying information about their own office's social network, compared to those where they are positioned.

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Additional to physical space, the routines of individuals play a key role in affecting their reach. Consider eating lunch in an off-site restaurant compared to eating in the office canteen. Joining others in the canteen would offer a wider reach to those who opt not to go out for lunch with a particular individual. A person going to lunch with a small group of individuals has less reach in their exposure, and would fail to be as accurate as those who frequent the canteen with the rest of the staff, since they do not witness the interactions of individuals and cliques in the canteen.

6.2.1.2 Frequency

The *frequency* mechanism is similar to reach, however, it highlights the repetition of exposure, and thus the confidence of encoding and recall of social networks. An individual might have wide contact in the organisation, but if these interactions are not repeated or frequent, the encoding might fade. With frequent interaction, the patterns would be encoded in a more lasting manner.

Being exposed to a relation once might suffice to generate an accurate perception, particularly if the observed relation lasted. For example, consider a new employee observing two colleagues going to lunch together. The observation might be encoded as those colleagues being friends that might turn out to be true. However, observing new pairings between those colleagues over lunch in the coming days would lead the observer to realise the error, and that the original observation was an outlier in a broader pattern. Relations are ephemeral but tend to form patterns over a longer timespan (Krackhardt, 1987*a*). Thus, frequency is an important part of encoding social relations accurately.

6.2.1.3 Pattern

Pattern exposure adds another level to reach and frequency of exposure. In dealing with attention and memory, people use heuristics to simplify complex information. One such mechanism is balance, which explains why people prefer to balance triads in memory (Koehly and Pattison, 2005). However, it is possible to override these heuristics if there is enough information to the contrary. For instance, Janicik and Larrick (2005) have shown how exposure to structural holes, as a particular social network pattern, enables individuals to be able to recognise structural holes in new networks.

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Exposure to rare and unexpected patterns in social networks is, therefore, important in helping the observer become accurate beyond chance in ascribing expected structural patterns, such as a balanced triad. Figure 6.1 illustrates the average performance of individuals on both advice and friendship relations in organisations. The figure distinguishes between interpersonal and structural acuity, as well as the effect of different criterion networks. Structural acuity is consistently higher than interpersonal acuity, since structural acuity captures general patterns of relations, and does not penalise errors on a dyadic level. People might be better at identifying such general patterns, because it relies on heuristics such as balancing triads. Additionally, applying an expert method (PCA) delivers higher average acuity scores. Methods, such as PCA, attempt to take local social expertise into account, and does, therefore, not penalise errors on relations at a distance. Key to the figure is that, apart from PCA, all measures result in an average that is below chance (0.5). Yet, there are certain individuals who can recall social relations better than chance. This is particularly the case with structural acuity that might be because of more frequent exposure to certain network patterns, since there are fewer respondents above the 0.5 threshold when considering interpersonal acuity. It is also key to observe acuity measure outliers that are only present on the lower end of the scale that suggests that people are on average not oblivious of social relations, and that low scores might be because of spurious responses to the questionnaire.

6.2.1.4 Conclusion

These three mechanisms—reach, frequency and patterns—offer a mechanism to understand and operationalise exposure theory. However, a particular individual might have high exposure only through one mechanism that would not provide an accurate network perception. It is only through combining at least two of the three mechanisms that a person would have enough exposure to be able to meaningfully recall social patterns. Thus, to develop an accurate perception of the network relies on a reasonable reach. Repeated exposure to the same reach in order to develop an understanding of consistency of observed relations among dyads. Lastly, to improve the chances of correctly filling missing observations in memory, the individual need to be exposed to particular patterns of relations.

For example: a fleeting exposure to a structural hole might not suffice to learn to expect these structures in the future. Exposure to such structures needs regularity or, should be observed elsewhere to confirm that it is not anomalous. Likewise, once-off wide exposure

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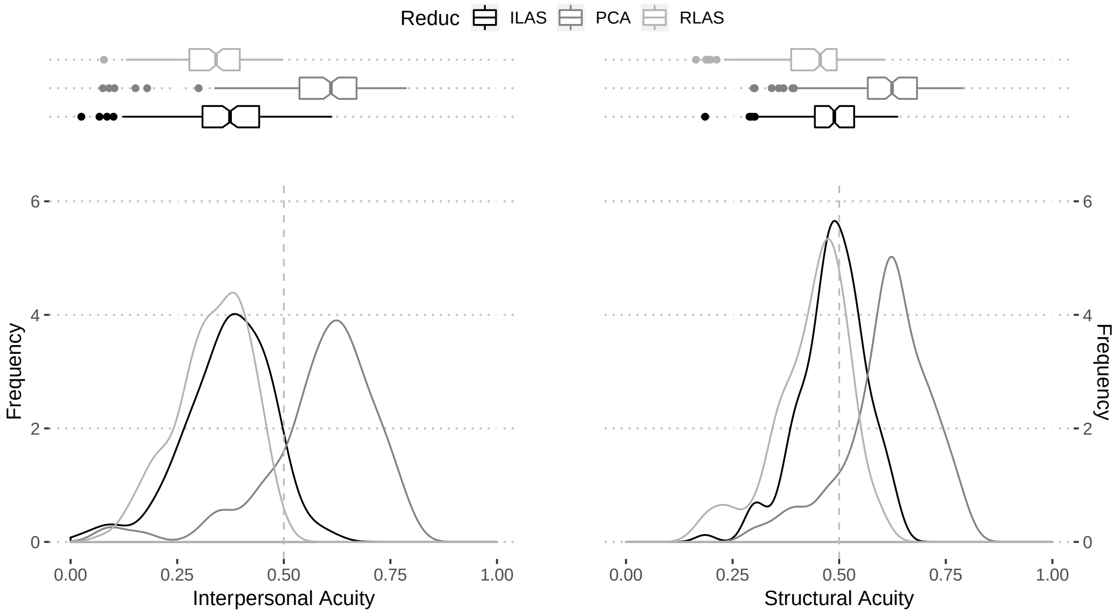

FIGURE 6.1: *Frequency plots, and accompanying margin boxplots, indicating the spread of acuity measures for idnividuals in the three datasets over both advice and friendship relations. The dashed line indicates the 0.5 accuracy threshold.*

to the network—such as a whirlwind tour given to new employees—would not offer any meaningful exposure. Lastly, highly frequent exposure, but with low reach—only a single alter—would not suffice to help improve acuity above the norm.

It is also important to note that exposure can either be direct access or conceptual exposure. Since information about a network could travel through a network, a well-connected individual could learn of relations without observing the relation. All three mechanisms could, therefore, operate through observation or information of observations. Consider gossip about others in the office, or a comment from a colleague that: '*they are friends*'. New employees, might have to rely on pure observations and singular informants of relations beyond their observable network. Likewise, senior members of the organisation also rely on informants of relations beyond their observable network.

To reiterate, exposure theory, therefore, explains that individuals come to learn of social relations in their network due to their position in the network. Certain positions offer less exposure than others, and thus offer a structural benefit to the position in the form of SNC acuity.

Lastly, consider the structural theory of Burt (1982). A key proposition from the theory

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is that individuals in similar social network positions, should have similar experiences of their environments. Their position dictates their exposure to information, and purposive action available to them. Exposure theory is, therefore, a more local variant of the standard structuralist theory developed in network science.

Exposure theory, therefore, captures the intuition of the majority of SNA scholars within the structuralist tradition. As many have highlighted (see Kilduff and Krackhardt, 1994), it is possible to accomodate agency within the structuralist agenda. In keeping with this drive to reintroduce agency for individuals within the structuralist framework, the following section proposes networking theory with which to understand empirical findings as well as open up new questions for future investigation.

6.2.2 Networking Theory

In contrast to exposure theory, networking theory ascribes more agency to the individual in directing their circumstance, while acknowledging the role of structure.[2]

Giddens (1984) offers a key distinction between *structures* and *systems*. Structures consist of *rules* and *resources* that are organised by individuals as properties of larger social systems. Systems are relations between social actors or collectives.[3] Structure is unattached to time and space, and exists through individual "memory-traces" (p. 25 Giddens, 1984).

The *rules* of structure are procedural in nature and definitive of the social praxis. Social agents use rules to guide action within a context, such as the rules to chess. However, this relies on mere awareness and the common implication of the codified rules of the context. Giddens (1984) envisions rules as mathematical formulae, not with the implication that social rules can be reduced to a mathematical formula, but that only in understanding the rule, which produces a well-defined outcome, could the agent utilise agency. Merely citing the formula, or observing the pattern of outputs to such a formula does not equate to social competence or knowledgeability of the rules. Resources from structure, are either *authoritative* or *allocative*, where authoritative is power over people, and allocative is power over resources.

[2] Structuralists do not completely ignore agency, they would rather argue that an individual has agency but within constraints of their environment (Borgatti *et al.*, 2014; Haines, 1988). As will be highlighted through structuration theory, individuals achieve agency through competent and knowledgeable interaction with the system (network).

[3] Structuralists, when invoking *structure*, refer to a *system* in Giddens' definition. System and structure is used interchangeably within structuralist context (Haines, 1988).

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Social actors need to draw from the structural features of wider social systems when entering a new system. These structures hold certain rules and resources that enable the actor to interface with the system by guiding their actions.

Consider a new employee of a professional services firm. Such an employee could draw from structure of their training in the professional praxis, and socialisation of general societal praxis, which could include common courtesy, knowledge about standard hierarchical ranks of titles, and standardised roles. They could identify positions available to them by, for instance, identifying their own hierarchical position. Using their understanding of structure, such a person would be able to function within a new social system. Over time, if their application of rules and resources from employed structure is accurate, they would fit within local systems of relations. Substantively, consider the scenario of a new employee who is *out of line*. Being out of line is an exclamation of their poor interpretation of structure, i.e., poor interpretation of appropriate rules and resources. Such an employee would not readily be included in the social system of relations.

The distinction between structure and system offers a framework for networking in this context. A competent social agent, with appropriate knowledge and application of rules and resources of the structure, would be able to gain agency. Agency is acutely linked to power, since agency is the ability to change one's environment (Giddens, 1984, p. 14). If a social agent is competent and knowledgeable of the appropriate application of structure in the system, they would be able to affect the system. Therefore, those who have agency, have power, since they are capable of uncovering and utilising social positions within the system that was previously unexploited or unsaturated by others. Only through learning of the system would an agent be able to purposefully position themselves.

Consider, again, that some people seem to be better at uncovering and understanding informal social relations. This ability, if not ascribed to their position, can be traced to either their natural ability, or a motivation to spend above average effort to understand and utilise the network, or exert agency in the language of Giddens (1984). The first, natural ability, is the area of psychology. The second is networking, which is well within the realm of sociological enquiry, and is exactly what is highlighted by *structuration* of Giddens (1984). A contextually helpful and relevant label for the use of knowledge of the social system, or network, is *networking*.

Again, focussing on Figure 6.1, a structural measure of perception results in higher average social acuity, in particular it tends towards 0.5. However, a structural cognitive rep-

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resentation above 0.5 accuracy is achieved more frequently, compared to interpersonal accuracy. This suggests that individuals share structural representations of the system, where some are more attuned to the actual system, thus earning accuracy scores above 0.5, which offers ability to have agency within the system, or in other words, they can network effectively.

6.2.2.1 Defining Networking

Two recent reviews offer insight of how literature has approached the concept of networking. The first is Gibson, Hardy and Buckley (2014), who focus on the concept within organisational studies, and the second is Porter and Woo (2015), offering a review of the concept mostly from psychology literature. Porter and Woo (2015) compiled a framework of four explicit conceptualisations of networking studies: networking for work performance; networking as career management strategy; networking as job search strategy; and networks as behaviour to develop professional networks. They further developed a networking theory that is modelled on social exchange theory that focuses on the dyadic relation.

Gibson *et al.* (2014) offer a helpful definition of networking: "*a form of goal-directed behaviour, both inside and outside of an organization, focused on creating, cultivating, and utilizing interpersonal relationships*" Gibson *et al.* (2014, p. 150). There are two clear signals within their definition. First, individual goals are assumed to direct the activity of networking, and second, networking is an instrumental activity of engaging with relations in a social network. The first implication is clear, goal systems of the individual drives networking. However, the goal system need not be as explicit and specific as they propose. All individuals do some form of networking, since it is a fundamental part of socialising. Some might be more explicit with their goals of networking, and thus their networking activities.

The second implication of the definition could be amended to highlight that networking does not need to entail explicit network connections. Networking, as defined by the authors, conjures up an image of an individual frantically connecting to as many people as possible through becoming their friend, or asking for advice, with the promise or goal of advantage. This implication, therefore, needs more scrutiny.

Porter and Woo (2015) only implicitly include relations beyond the dyad in their conceptualisation of networking. They propose that, during the *growth* stage, individual partners gauge each other's value to decide whether they would reciprocate a relation and carry on to the *building* stage. Much of transactive memory systems, such as with Porter and Woo

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(2015), limit network value to the dyadic level. There is, however, value beyond the dyad in networking. From the social capital tradition, much of social capital is to be found beyond the dyad. Thus, explicit dyadic connections are not the only observable networking benefit. One must investigate individual conceptualisations of the network beyond the dyad, since an explicit dyadic connection might be motivated on a triadic level. In other words, becoming friends with the CEOs son, or basking in reflected glory, does not assume the value to be in the dyadic connection to the son, but rather of triadic value of the CEO father.

Networking, therefore, involves gaining knowledge about explicit connections between others in the network, and not necessarily engaging with alters. This idea is well captured by considering an *activated* versus *mobilised* network (Menon and Smith, 2014; Smith *et al.*, 2012). An activated network is an individual's perception of the network as a whole, whereas a mobilised network is actually direct interactions with alters in the activated network. Knowledge about connections within a network are an additional source of value to the individual by helping them understand the general, or specific, social environment, without direct interaction. In fact, it could be argued that a general conceptualisation of network structure is a prerequisite to successful networking, since without such knowledge, the *networker* is consigned to randomly connect with the hope of striking social capital gold. Networking is conceived as a purposeful non-random activity.[4] The role of explicitly connecting with people should, therefore, not dominate the conceptualisation of networking. This pre-conceptualisation of the network, therefore, acts as a prior to actual networking behaviour or mobilisation. It also closely relates to the role of structure within a system from a structuration perspective.

The definition provided by Gibson *et al.* (2014) can, therefore, be updated. Networking is behaviour that is mediated through both the conceptualisation of the network and contextual antecedents to establish connections both inside and outside an organisation. The objective of the process is focussed on encoding, creating, cultivating and utilising interpersonal interactions. Given that SNC acuity influences networking, the next section investigates the mechanisms of networking behaviour.

6.2.2.2 Mechanisms and Consequences of Networking

Consider the helpful theoretical model provided by Gibson *et al.* (2014, p. 153) that illustrates the antecedents, behaviour, mechanisms, and consequences of networking.

[4] Indeed, the non-random nature of networks is repeatedly shown (Barabási and Albert, 1999).

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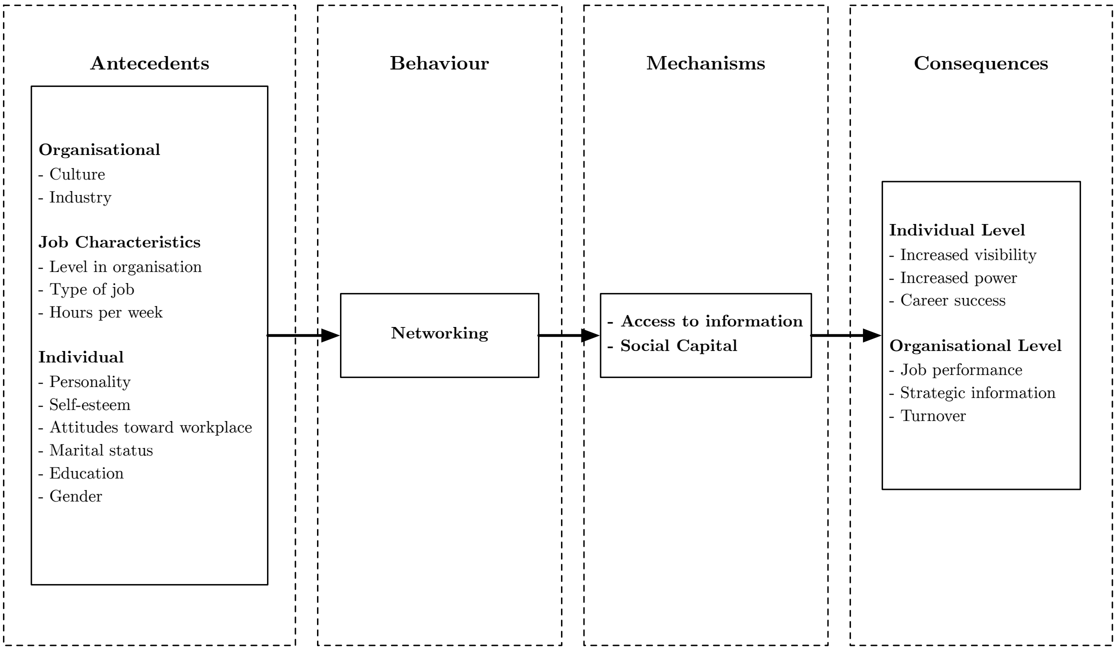

FIGURE 6.2: *Theoretical networking model, adapted from Gibson et al. (2014)*

There are two key points to raise related to the framework. First, an antecedent to networking can also be network acuity. Second, the mechanisms, and consequences of networking are of particular interest here. The first point is evident from the arguments offered above: a cognitive model of a social network is a necessary and predictive prior variable in networking behaviour. The second point is worthy of more exploration.

Gibson *et al.* (2014) proposes access to information and social capital as mechanisms of networking. Access to information can be gained through establishing many connections, whereas social capital can be gained through building instrumental or expressive connections—as in the formulation of Lin (1999)—such as becoming friends with the CEO's son. Social capital would here relate to what Lin defines as "*access to and use of resources embedded in social networks*" (1999, p. 30), with the explicit premise of "*investment in social relations with expected return*". Further, Lin explicitly talks of networking as an activity of gaining social capital, and offers four elements of such a mechanism: *flow* of information, *influence*, *social credentials* and *reinforcement*. *Information* is gained through actively positioning oneself within network structure, specifically "*strategic locations*" within the network or the hierarchy (1999, p. 31). The second element, *influence*, is gained through particular positions either formal or informal that enables the occupant to wield influence over others. The

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third, *social credentials*, is gained through being affiliated to a credential position or *alter*, and gaining some benefit through the extension. The final element, *reinforcement*, is benefit gained from understanding the network and the reinforcing effect of establishing and reinforcing individual identity. As an example, consider networking activities, of which the only goal is to find the networker's place within the network, and not necessarily establish any connections for access to the flow of information or connecting to a particular powerful or influential *alter*.

The mechanisms from Figure 6.2 should, therefore, either be collapsed to only contain social capital, since the concept can encompass access to information, or the mechanisms should be extracted into discreet elements as above. Doing either is not instrumental here. It is important to specify that one particular mechanism of interest is network position, and that it is only one of many.

As noted, networking theory remains sensitive to the role of structure in social environments. Thus, the mechanism of networking is to enhance the individual's structural position, which offers multiple benefits. Consistent with Giddens (1984), the act of networking is regarded as agency, since the individual is able to change their environment, and particularly the social system, by establishing or rewiring connections between social entities. Since agency is only available to the competent and knowledgeable social agent, where competence and knowledgeability are about the perception of the social system, it is only through an accurate perception that an individual can network *successfully*, through *purposeful* action.[5]

6.2.3 Contrasting Exposure and Networking

Highlighting the degree of ascribed agency achieves a contrast between the two theories. Exposure theory offers limited agency to the individual while networking theory emphasises agency. Exposure theory is, therefore, closer to the traditional structural determinists, whereas networking theory offers a reconsideration of the role of agency within structuralist thought.

Exposure theory does not ignore the resources embedded within the network, these resources and constraints are key to structural thought. However, networking theory ascribes

[5]The two limitations, *successful* and *purposeful* are highlighted, since all social agents can network unfettered, and it is reasonable to expect that with enough random networking, an individual could be expected to establish a favourable position by chance.

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agency to the individual as an extra parameter in reaching and managing these resources. It is, therefore, not pure exposure, but behaviour that improves an individual's access to and utilisation of social capital. Most important here, when contrasted against networking as perceived by Gibson *et al.* (2014), networking has a cognitive aspect that does not necessarily involve explicit connections or exposure. As noted, social capital also comes in the form of a cognitive representation of self within the network. Social capital does not require any explicit exposure or connections, but merely an accurate representation of the network environment. Or, as conceptualised by Giddens (1984), a competently and appropriately applied structure.

Recently, Kuwabara, Hildebrand and Zou (2018) offered a convincing framework built on lay theories of individuals about networking. In summary, individuals either regard networking behaviour a fruitless exercise, or a key mechanism to social advancement. Lay theories, therefore, broadly follow the structure-agency distinction. Some individuals believe that their social position, and, therefore, social capital, is mostly a given (structuralist), whereas others believe that social position and social capital is a malleable outcome (agency). Many, who believe that social capital is fixed, do not ignore the behaviour of networking, but consider it unnatural and artificial, with any benefits mostly due to chance. This is an interesting thought, and helps contrast exposure and networking theories by highlighting motivation as a key underlying factor in networking behaviour. Shea and Fitzsimons (2016) also highlight the importance of motivation.

Both theories highlight a central point: network position is related to social network acuity. However, where they differ is the direction of the relation.

Networking theory proposes that an individual reaches a beneficial network position through successful networking behaviour, but only if mediated through accurate perceptions of the network. Casciaro, Gino and Kouchaki (2014) introduced networking as a strategy for individuals, in SCNA that supports the idea that networking creates a lens for agency in social network analysis. However, networking is yet to be explicitly linked to social network position as an instrumental goal, although the hypothesis is theoretically supported. Networking theory is, therefore, an alternative to exposure theory for network acuity, and it is proposed here that networking theory is better able to explain the empirical findings from prior research as well as the findings from the previous chapter.

To conclude, networking theory states that individuals develop a cognitive representation of their social networks to utilise the knowledge of the relations for their benefit. The

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benefit can be conceptualised as social capital as presented by Lin (1999). Of particular interest is the curation of particular relations, and relative positioning by a social agent to improve their social capital. These efforts would result in an individual gaining advantageous network positions that is usually measured through centrality measures. Successful networking behaviour is, therefore, reliant on an accurate network perception. However, not all individuals have accurate perceptions of social networks, leading some individuals to be capable of networking more successfully. The main proposition is therefore that an individual with high SNC acuity would position themselves centrally, where such positions offer social capital for their benefit.

6.3 Empirical findings

It is helpful to summarise the key empirical findings from prior literature and Chapter 5. The key finding is that social acuity relates to informal social network position, supporting prior literature (Bondonio, 1998; Casciaro *et al.*, 1999; Grippa and Gloor, 2009; Krackhardt, 1990; Krackhardt and Kilduff, 2002; Romney and Faust, 1982). Prior literature also found that formal positions in the organisation, when investigated, either have a negative relation (Casciaro *et al.*, 1999) or a neutral relation (Krackhardt, 1990) with social network accuracy. These relations are revisited in Chapter 5, with the exception that the assumption of direction of causality is reversed. The problematising finding in prior research is that formal position does not relate to social network acuity. The problem is that the given explanations for this particular finding could not properly be explained within the theoretical model of exposure theory. Exposure theory successfully explains why social position leads to accurate social network perceptions, but fails to explain why this is not observed when focussing on the interaction with formal positions. This is further problematised by showing that formal positions can be considered as extensions, or similar to, informal network positions, and should, therefore, similarly be exposed to network information. To illustrate formal positions as an extension of informal network positions, a network correlation in Table 5.18 indicates that formal position is significantly related to informal positions in the advice seeking network.

As a key example, Casciaro *et al.* (1999) found that hierarchical level negatively affects accuracy on the advice network. The same study found that hierarchical level is significantly related to informal social position in the advice relation—advice centrality—which

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should be predictive of accurate network perceptions. They deal with this contradiction by highlighting that "*higher-level employees may not desire, or need, to gain power through an accurate perception of the organization's informal structure. Higher-level employees are more powerful than other members of the organization by virtue of their formal position*" (Casciaro, 1998, p. 345). They, therefore, ascribe agency—in the form of power—to individuals in a hierarchical position—a proposition from networking theory—and counter to their adopted exposure framework.

The findings in Chapter 5 confirm no relation between formal position and social network accuracy for both advice and friendship. If exposure theory is consistently applied, then individuals in formal positions should not lose their ability to gain accuracy through exposure to the network. Individuals in formal positions remain exposed to the network, as indicated by their centrality in advice networks, and should be able to encode and recall the network relations. However, while formal position is significantly related to higher centrality, there is no relation between formal position and advice acuity. Exposure theory can, again, not sufficiently explain the empirical observations. The question for networking theory is then: why are individuals in higher formal positions less accurate, or have no relation with accuracy?

There are three reasons for this. *First*, the result might be from sampling bias, especially considering networking as the theoretical lens. *Second*, an individual's attention might be diverted to a wider or focused network that is more relevant to their formal role in the organisation. *Lastly*, they do not have to network for power and prestige, since a higher formal position formally provides these benefits, or in other words, their motivation is removed.

When observing a department (such as with Pharma) or an organisation (such as SilSys) there are fewer observations of higher positions. The individuals in higher positions might be more accurate than observed, but their expertise might be on a smaller subset consisting of their peers, superiors or industry stakeholders, who are not observed in the datasets. The observation that there is a negative relation between formal position and SNC acuity could, therefore, be an artefact of the sample. In other words, the higher a person in the hierarchy, the less their valued network is captured, resulting in a negative relation between hierarchy level and SNC accuracy.

Gibson *et al.* (2014) offers some ideas as to why individuals higher in the formal hierarchy might be less attuned to the local social network. They include organisational level as an

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antecedent to networking behaviour, and offer the idea that networking efforts might be shifted to where it would offer more benefit. Since a person is endowed with power and status when entering a formal position in the organisations, they would most probably start to focus their networking efforts elsewhere in the organisation. If the person is a manager in the department, their networking efforts might shift to an inter-departmental focus. If an individual is at the head of an organisation, they might shift their efforts towards other organisations or within the industry. Networking pay-off is therefore relative to an individual's position within an organisation (high or low status), and has less to do with exposure. Consider the examples offered by Gibson *et al.* (2014, p. 154) after highlighting that individuals higher up in the organisational hierarchy network more and have larger networks than those lower down: "*As an individual advances in an organization there may be an expectation to develop new clients, be involved in professional societies, and take on more visible projects in the organization*". These are all activities that would take networking efforts away from the immediate organisational context, and thus possibly have a negative impact on their measured accuracy.

Consider that power is closely related to higher formal positions, since higher formal positions offer more power and increased status. Two studies attempted to link power and identity to social network activation.[6] The first study by Smith *et al.* (2012) indicated that high-status individuals activate wider networks. The second by Menon and Smith (2014) specified identity, rather than power, to be explanatory in the wider activation during changing circumstances.

The key contribution by the two studies, for the purposes here, is that network perception links to identity by finding that: the more assured a person is of their identity, the wider their network activation. In networking theory, this would mean that if a person's identity is formally recognised (such as with formal organisational positions) they could disregard their immediate social environment in their networking process, since they inherit the resources and rules through their position, and should spend efforts elsewhere. This also explains why formal position, or status, was first identified as the causal factor, with only the second study confirming the actual mechanism: identity confirmation.

Formal positions do not necessarily have to lead to network activation beyond the immediate environment. It could also, reasonably, nullify the need for networking. Consider

[6] The activation of social networks is the recall of respondents of their social network. Social network activation is observed by offering respondents a free-recall survey of social relations.

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therefore, the implications of gaining power through formal positions from a structuration view. Any extra needs of structural resources not granted by the position could easier be established from such a position. Individuals in such a position do not need to establish an accurate network perception to gain agency to establish and rewire relations. Agency is achieved through a formalised position, as such. Acuity is less important over subordinates, since they are subject to the inherited privileges of the position. In general, formal position offers a position within the social system. The position inherits the appropriate rules and resources needed to operate in that particular system. It also relieves most needs to further interpret the social system, since the formal position is entreched in the organisational rules and resources that come natural to the social agents involved.

Consequently, it could be argued that an individual in a formal position does not need to network to develop an advantageous position within the network in focus, since they are formally given power and prestige, or in more general terms, social capital. Consider some explicit cases: An uniformed officer does not need to network to exert authority over civilians. The officers are formally provided the position within the social structure that is endowed with the resources and prescribes the rules. However, when a group of individuals meets for the first time, the same officer, without uniform, would have to revert to networking to achieve the same power. Moreover, the same uniformed officer needs to network among other uniformed officers to gain an influential position. Formal positions, therefore, take care of many of the needs of networking by simplifying and signalling the expectations for everyone involved. This frees up the individual in the formal position to focus their attention on other tasks, without the need to keep tabs on social relations to perform their duties. Chapter 5 illustrated in Table 5.26 that formal positions have a negative effect on informal social positions on the friendship relation, whereas Table 5.25 showed a clear positive relation between formal position and radial measures of centrality, when considering advice relations. The substantive conclusion would be that individuals in formal positions are approached more for advice than those that are not in formal positions. They, therefore, enjoy prestige and control on information flow due to their formal position. Evidently, according to exposure theory, these individuals should have been more accurate about the network relations, since they hold a central position in the advice relation. This is, however, not the finding of prior research nor the current empirical evidence.

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6.4 Social Network Cognition

This section aims to draw increasingly broader conclusions by relating the above findings to the wider field of SNC research. Recall from Chapter 3 that dividing the literature into antecedents and consequences of SNC provides a convenient delineation of the field. This section will focus on the consequence literature, with little coverage of antecedents. The reason is that antecedent studies focus on factors that cause particular network perceptions. Since the focus is here on networking theory, which is primarily a theory of the consequences of network perception, the antecedent studies are only important for the exploration of reasons for why accurate social network perceptions are developed.

6.4.1 Network Position as A Consequence Of SNC Acuity

First, consider the seven studies that, to various degrees, linked SNC to observed outcomes.[7] There are three broad outcomes, performance, leadership, and power. Leadership is not empirically tested by Balkundi and Kilduff (2006), but it is a proposition that SNC acuity is itself a leadership trait. Little research has followed up on this proposition, the closest being Brands *et al.* (2015), who found that men are perceived as leaders in centralised networks while women are favoured in more decentralised networks.

The two highlighted studies that relate SNC acuity to power, do so differently. The first, Krackhardt (1990) investigates SNC acuity as a source of power itself. It is important to note that power is strictly *perceived*, since they measured an individual's power as perceived by others in the network. The second study by Simpson *et al.* (2011*a*) is interesting because it relates to power, but not as an actual outcome of acuity. They investigated how power acts as a mediating variable on the benefit of accurate network perception. They found that an accurate network perception is only valuable to an individual in a lower power position, but only if there is asymmetry in acuity among peers. What is interesting is that improving information of the social network for the high power individuals did not significantly improve their outcomes. This can be interpreted as the reason individuals in higher power positions have less return for their cognitive investment when they are in the minority of the network. This is a key insight to understand the apparent lack of motivation for networking or low SNC acuity for individuals higher up in the organisational hierarchy. Moreover, it confirms the implications of networking theory, which highlighted

[7] For reference see Table 3.2 in Chapter 3, on page 59.

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that formal power nullifies the need for networking to gain agency, since they are afforded such advantages already.

What this translates to is that individuals might have a learnt response, or heuristic, to being placed in a power position that results in the loss of motivation to encode the network. This might be due to experience showing that networking offers little benefit. Moreover, the inverse is true for those in a relatively lower position. Networking, for them, carries much more benefit, but only if some asymmetry remains. This relates well to the findings of Hahl *et al.* (2016) discussed below.

Performance, as an outcome of SNC acuity, enjoys more investigation (Hahl *et al.*, 2016; Ho and Sze-Sze, 2009; Kilduff and Krackhardt, 1994; Marineau, 2017). Performance is generally measured within an organisational context, where an individual's performance is measured on aspects such as promotions, or through ratings by peers or superiors. Some studies focussed on particular aspects of SNC that are not related to acuity. For example, Kilduff and Krackhardt (1994) investigated whether being perceived as a friend of a successful *alter* would boost the perception of one's own performance. Nevertheless, such findings create interesting questions related to networking. For instance, if an individual knows that they can *bask in reflected glory* then would they, as part of their networking repertoire, ensure that others perceive this to boost the appearance of performance, or would they befriend the target individual and let the basking effect take its natural course? All of this is only possible if the networking individual has an accurate perception of network relations. Ho and Sze-Sze (2009) investigated the effect of SNC acuity on job performance, but did not find a significant relationship. They did find that expertise recognition was predictive of job performance, which is interesting when compared to the insights of Kilduff and Krackhardt (1994). More recently, Marineau (2017) investigated and confirmed that SNC acuity of trust relations positively relates to promotion prospects. Recall that job performance and career advancement are consequences for the proposed framework of Gibson *et al.* (2014). Networking theory is, therefore, favourably positioned as a theoretical mechanism to explain how cognitive effort around social networks might lead to benefit the individual. Performance is, therefore, not the result of networking, but mediated through the activation of agency through networking. Agency allows individuals to find, if it is available, social positions that are thought to provide benefit. Moreover, performance should be separated into immediate and delayed measures. Immediate measures of performance are non-dynamic measures, such as those used by Ho and Sze-Sze (2009). Delayed measures are dynamic. It

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takes longer to realise, or is measured infrequently, or with delay such as promotions, as used by Marineau (2017).

Consider two networking strategies by an individual. The first relies on uncovering social network relations that might reveal favourable social positions, requiring the establishment of beneficial connections. Over time, a series of positions would have opened. With appropriate positioning, certain advantages could be gained, such as hearing news first (closeness centrality) or adding novel insights (betweenness centrality). These actions might be enough to help the individual gain a promotion in time. The second strategy could be to commit to a similar process, but rely on the occupied position to be formalised over time. This could be regarded as a rent-seeking strategy. These benefits will be secondary, and necessarily delayed, to any networking behaviour.

Lastly, Hahl *et al.* (2016) investigated how asymmetry of network awareness relates to disintermediation. The hypothesis is that for an individual to bridge a structural hole, the alters for whom they mediate must not have any knowledge of the asymmetry, otherwise they could take steps to disintermediate. These brokerage positions are also found to offer higher returns. As such, more accurate network perception leads to occupying a social position that offers more returns. Compare this finding with that of Simpson *et al.* (2011*a*). Both studies illustrate that there must be some asymmetry of network acuity to offer benefit for individuals. Hahl *et al.* (2016) did not formally frame their study in such a way, but they offered evidence that SNC acuity might lead to network positions. Additionally, Simpson *et al.* (2011*a*) offered the insight that individuals with formal authority do not have much benefit in developing accurate network perceptions, especially when compared to the potential benefit to those with less formal authority.

Again, consider the key proposition of the section: network position for an idnividual is gained through superior network acuity of the individual. This is achieved by arguing that an individual with more accurate SNC would be able to position themselves more successfully into favourable network positions, where these network positions offer more structural advantages to the occupant. This is a reasonable scenario that can be envisaged within the context of the brokers of Hahl *et al.* (2016). Here, the brokers have more information of the structural hole, and can, therefore, position themselves into such a position, where this position offers them the well explored benefits of bridges.[8]

[8]Bridges can be conceptualised by both SWT and SH theory, which offer a theoretical motivation, and have produced multiple empirical verifications of the value of bridges.

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A key question here is how an individual can position themselves? This is well explored within the networking literature Gibson *et al.* (2014). In networking literature, networking behaviour is directly linked to positioning acts. Networking could consist of actively connecting to individuals, establishing a cognitive map to understand social contexts, or linking other people. In other words, an individual can become friends with a perceived popular or high performing person—in order to bask in their glory—or become acquainted with someone who might benefit their existing network and thus form a bridge. These acts are behaviours that explicitly change the network structure to the advantage of the networking individual. However, non-explicit networking is also feasible and beneficial, as shown by the experiments of Simpson *et al.* (2011*a*), since individuals were only made aware of exchange relations between others in the network—they did not get more exchange partners, or a special position—they benefited from knowing others are connected, and could plan accordingly.

6.4.2 Antecedents reviewed

Literature categorised into the antecedent grouping investigates the causes for particular network perceptions, whether individuals are accurate (Casciaro, 1998; Casciaro *et al.*, 1999; Flynn *et al.*, 2006; Freeman *et al.*, 1987; Janicik and Larrick, 2005; Krackhardt, 1990; Neal *et al.*, 2016; Simpson and Borch, 2005; Simpson *et al.*, 2011*a*,*b*), congruent (Heald *et al.*, 1998; Krackhardt and Kilduff, 2002), or have systematic patterns (Flynn *et al.*, 2010; Krackhardt and Kilduff, 1999; Kumbasar *et al.*, 1994; Menon and Smith, 2014; Smith *et al.*, 2012). Six general antecedents are investigated: network position (i.e. Casciaro, 1998; Grippa and Gloor, 2009); heuristics (Kilduff and Krackhardt, 2008; Kumbasar *et al.*, 1994); personality (Casciaro *et al.*, 1999; Flynn *et al.*, 2006); gender (Neal *et al.*, 2016); and formal position and power (Simpson and Borch, 2005; Simpson *et al.*, 2011*b*). This thesis proposes social network position, particularly centrality, as the result of higher network acuity. It is therefore prudent to review the proposed antecedents, particularly for acuity. The implications relative to Casciaro (1998); Grippa and Gloor (2009); Krackhardt (1990) are well covered earlier in this thesis and would not be revisited.

Freeman *et al.* (1987) proposed, in response to the BKS critique, that individuals recall long term repeated interactions, as well as more significant interactions. This would mean that there is a level of exposure and motivation that play a role in the accurate encoding

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of social relations. Freeman *et al.* (1987) focussed on the difference in commission errors between an in-group and out-group member. Those present in the office complex of the colloquiums defined the in-group members, who are expected to have the most experience of colloquiums. They summarise the results: "*It seemed that although we asked the question 'Who was there?' the question our informants actually answered was more like 'In a typical setting like the one we're referring to, who is likely to be there?'*". Individuals seem to apply a general mental model of who would most likely have attended the colloquia, instead of recalling actual observations or interactions. Thus, if this is extended to comment on antecedents to acuity, it would first define acuity to be a contextual representation of long term significant relations, i.e mental models. Recall is, therefore, not necessarily based on actual exposure to individuals, as exposure theory would suggest. It is also prudent to highlight that the study did not investigate social relations, but only co-occurrence at an event. Also consider the possibility that the in-group in the study might also be the more central individuals in the social network, when considering degree centrality. Thus, if centrality and accuracy were measured, it could report a relation between central network position and acuity.

Another key investigated antecedent is personality types. Casciaro *et al.* (1999) investigated the role of *positive affectivity* in determining acuity on both a global and local scale. They found partial results that confirm improved acuity on a global scale, but this might be due to spurious responses. Flynn *et al.* (2006) was able to highlight a strong link between the need for social status by self-monitors and network acuity. Individuals with a high need for social status are motivated to exert agency in their environment. They are, therefore, more attuned to the social dynamics and social system that enables them to identify dyadic relations of power differentials. In attaining social status, such individuals would need to associate themselves closer or relative to higher status individuals, which is descriptive of networking behaviour. Whether they are successful is beyond the scope of the study of Flynn *et al.* (2006), but their command of network dynamics is confirmed. Need for social status is, however, not a personality type—Flynn *et al.* (2006) actually investigated self-monitoring.

Other relevant studies are Smith *et al.* (2012) and Menon and Smith (2014). Through experiments, Smith *et al.* (2012) tested the effect of the threat of job loss on an individual's activation of their network. Two groups, *high* and *low* job status, were tested. They found that those with higher status jobs activated larger and less constrained networks when faced with the threat of losing their jobs. Low status individuals, however, activated smaller and

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denser networks. In a later study, Menon and Smith (2014) wanted to experimentally test the mediating effect of power and identity for social network activation. They found that being primed of an identity resulted in activating a broader social network, whereas power had no effect.

This helps to understand why SNC acuity decreases as an individual moves up in the organisational hierarchy. Their activated social networks are wider and less constrained, with perhaps little relation to their actual workplace. Inversely, individuals lower in the hierarchy, have smaller and more constrained networks intimately tied to their workplace. The experiments of Menon and Smith offer another clue in that it is not necessarily the power of the position that affects activation, but an individual's identity, whether it is powerful or not. If hierarchy in an organisation begets power, the formalisation of social position, and thus confirmation of social identity, enables wider activation of networks that might be outside of the observed networks of CSS studies.

6.4.3 Conclusion

There are two key points to raise in conclusion. First, consider that if exposure theory is strictly applied, it would mean that any networking behaviour is a fruitless exercise, whereas networking offers a more dynamic model of socialisation by offering both agency and structural boundaries.

6.5 Concluding Implications for SNA

In 1994, Kilduff and Krackhardt introduced the need to *bring the individual back*. They challenged the false juxtaposition between structural determinism and agency research. Most of SNA research has been driven, and successfully so, by the structuralist agenda. However, they proposed a new agenda to bring the individual back into the conversation. The reasons why the individual has been left out is because of the black box of psychology that most researchers wanted to avoid (Tasselli *et al.*, 2015). In 2015 Taselli and Menges joined Kilduff in echoing the previous call more than twenty years prior. This time, with momentum building on the agenda of including agency within SNA literature, they could report on some progress on research that sought to include the individual within social network analysis. However, research remained isolated with many doubling down on the structuralist

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agenda, and others developing almost an independent field. They conclude the paper with a proposal to blend the two streams. This proposal encourages a model where individuals and networks co-evolve. This thesis is a reply to this call.

Tasselli *et al.* sketches the following co-evolution scenario:

> "Individuals who are new to organizations find themselves embedded within existing informal and formal networks that display structural features such as small worldedness. The roles, identities, and network positions that individuals find available offer potential social interactions. These interaction possibilities call forth individual differences in personality, cognition, and other attributes represented" (Tasselli *et al.*, 2015, p. 1363)

This effectively describes what is proposed by networking theory. The authors, however, distinguish networking theory as a particular step in the process, where networking theory expands networking beyond behaviour, toward cognitive representation of the network. This extension is important, because espoused networks could effectively be as real as actual networks,[9] and the conceptualisation and cognitive representation of the network patterns are a part of the networking process.

Sasovova, Mehra, Borgatti and Schippers (2010) investigated the relation between self-monitors and network brokerage positions, and found that high self-monitors are more likely to attract friends (degree centrality) and occupy new bridging positions (high betweenness centrality or low constraint). Since high self-monitors have more accurate network perceptions (Flynn *et al.*, 2006), and that accuracy leads to radial and medial network positions, networking theory is supported. This thesis thus offers the link between accurate SNC and network position. As such, self-monitors—or those with status aspirations—have more accurate network perceptions that establishes agency for networking activities, leading them to fill advantageous network positions. This is as opposed to directly relating the self-monitor trait to network position. Oh and Kilduff (2008), reaching the same conclusion, found that high-self monitors are more probable to be observed in brokerage positions.

The proposed networking theory model in the light of the reviewed literature is illustrated in Figure 6.3. Sasovova *et al.* (2010) and Oh and Kilduff (2008) highlighted the relation between self-monitors and social network position, such as centrality and brokerage. However, this thesis proposes that self-monitoring leads to motivation, such as status

[9]This is known as the Thomas theorem also cited by Tasselli *et al.* (2015).

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attainment. Flynn *et al.* (2006), also showing this relation, found that self-monitoring leads to accurate perceptions of network dynamics. Having an eye for power dynamics would lead to accurate network perceptions in general, particularly identifying open and unsaturated network positions. Such an individual, therefore, develops the agency to be able to network and position themselves into favourable network positions, such as radial and medial positions and to reduce their constraint (be brokers).

The empirical findings in Chapter 5 supported the hypothesis that accurate network perceptions lead to network positions, and additionally supported the idea that formal position increases status and power within the networked social system that would, therefore, reduce the motivation to develop accurate network perceptions. The more formalised the position, the more it reduces the motivation, otherwise the networker should remain aware of the network dynamics to keep their social status. This is why acuity is related to informal social position, but not formal positions, since the motivation leading to the position is satisfied. Indeed, self-monitor and the need for status attainment could indefinitely perpetuate the loop, but there are limits to the social system. Once a person reaches a formalised social position, they could either be satisfied with their lot (perhaps due to a medium need for status attainment), or they could proceed to network by learning and understanding the social system, to establish agency, and consequently the power to affect the system (networking) to position within the new social system. Within datasets such as observed in Chapter 5, such an individual could be present, but the network in which they might be networking is no longer in scope. Those that do not have a high need for status attainment, could be satisfied with a generic conceptualisation of the network, and are thus limited within the system. Others could have a high need for status attainment, but are not high self-monitors,[10] which would lead them to perform networking activities, but would not be as successful.

[10] Thus not adept at understanding social relations beyond the generic.

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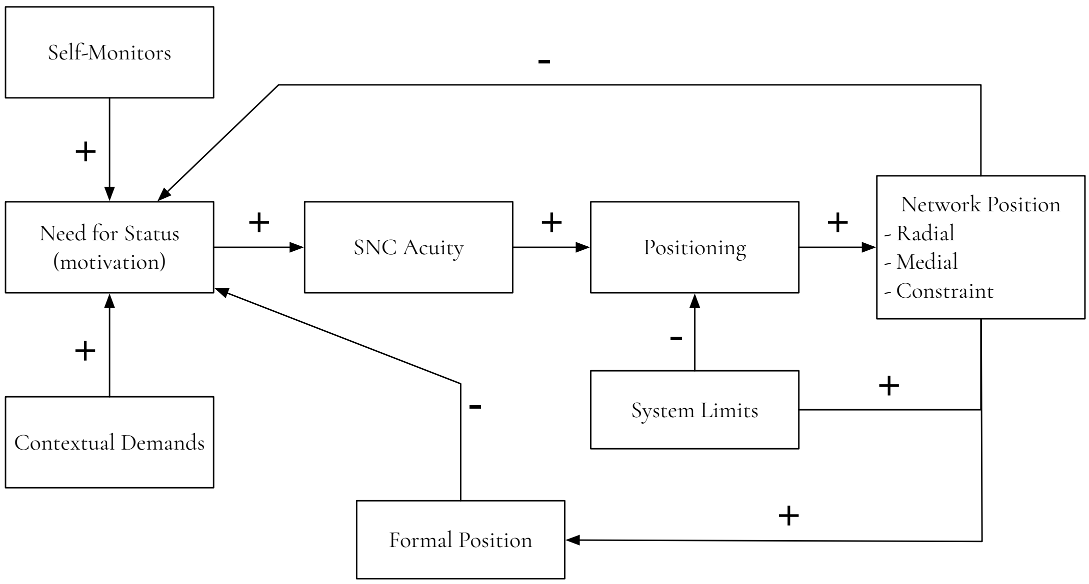

FIGURE 6.3: *Networking Theory Model of Network Position.*

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CHAPTER 7

CONCLUSION

7.1 Introduction

This chapter offers a brief and accessible conclusion to the thesis. This will be done by summarising the process and highlighting key points throughout the chapters. A key emphasis will be placed on the objectives and conclusions of each chapter, which is concluded by stating the primary question, and qualified answer of the central thesis.

7.2 Social network Analysis

The primary objective of the chapter was to introduce the reader to a field that is capable of offering the concepts and tools to investigate social networks. This was done by offering a brief historical review of the literature to substantiate the choice and offer concepts, theories and tools that became important in the later chapters. Apart from the introduced tools, concepts and definitions, two key ideas were important at the conclusion of the chapter. First, the issue of angency and the individual within the strong structuralist agenda. Second, there are two helpful network models that would recur throughout the thesis: flow and architecture models. The flow model enables the conceptualisation of networks as channels through which information flows, whereas the architecture model highlights the structural effects of networks, without the need for the flow of anything through the network.The final proposed networking theory model in Figure 6.3 is more congruent with the architecture model. This is an interesting conclusion, since the architecture model is closer to the pure structuralist agenda, where networking theory is proposed as an adaptation to a naive structuralist approach. This is because exposure theory relies on the flow of information in the network to develop accurate network perceptions i.e., information of the network flows more readily to those in central network positions. Networking theory, however, highlights that there needs to be no flow of information in the network, since individual agents, who are competent, knowledgeable, and motivated find structural positions to benefit from the

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inherited power, status, and prestige. This is highlighted by reiterating the decrease in acuity whenever an individual is in a formal social position.

7.3 Social Network Cognition

The chapter on social network cognition (SNC) research is introduced with the objective to review previous literature that investigated how people perceive social networks. The central thought, which is carried through the thesis, is the observation that individuals are less accurate than expected when considering social relations. Since social relations are central to complex social life, humans are expected to perform better than chance in recalling social relations. However, as with many other cognitive processes, encoding and recalling social networks are fraught with inaccuracies.

The review divides the literature into three parts: methodology, antecedents, and consequences. A key part of the literature is defining the specific needs for datasets, which enable investigations into how individuals encode, understand and recall information of social networks. Particularly important for the thesis is the definition of the cognitive social structure (CSS) dataset that was developed by Krackhardt (1987*a*).

The chapter further elaborates on two key groupings of literature that either investigate the *antecedents* for social network perceptions, or the *consequences* of perceiving social networks in particular ways. From the literature, a competing hypotheses and an yet to be formulated assumption becomes clear: structure dictates perceptions. Particularly social network position, such as centrality, predicts accurate network perceptions.

With further investigation into the literature, there are certain clues that indicate that the taken for granted structuralist assumption might be incorrect. These clues are evident in the empirical work that indicate that most findings hold within the forwarded theoretical lens. There is, however, a key empirical observation that does not hold. At the conclusion of the chapter, an empirical model is introduced, which would be able to confirm that the assumed direction of causality should be reversed i.e., an accurate network perception leads to advantageous network positions. This objective resurfaces the structuralist-agency debate that was highlighted in Chapter 2. This distinction would turn out to become important in the discussion of the findings in Chapter 6. The chapter concluded with three testable hypotheses, three of which needed to be supported to substantiate a revision of the causal direction assumption. These hypotheses are:

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H1a There is no significant relation between formal position and social acuity.
H2b There is a significant positive relation between formal and informal social positions.
H3b There is a significant positive relation between social acuity and social position.

7.4 Methodology

The objective of the methodology chapter is to explore and define an appropriate methodology to empirically test the three hypotheses. There are certain known requirements. First of all, the data needs to capture a full CSS dataset that captures friendship and advice relations. Three chosen datasets were identified and explained. The datasets offer similar social contexts (organisations), yet they offer the chance to test the hypothesis between different nuanced individual contexts that would improve the contextual validity of the findings. The three sites differ in their size, the boundary placed on the network, levels of hierarchy, and industries. It is a key limitation of CSS data that large populations are impractical to investigate and the number of CSS observations are therefore $N = 71$.

To test the hypothesis, three key measurements are needed; SNC acuity, informal social network position and formal position. Chapter 4 elaborates on two of the measures: SNC acuity and informal social network position. SNC acuity requires the researcher to establish a criterion network, to which individual perceptions could be compared. The chapter explores various options to establish a criterion network. This involves reducing a three-dimensional data structure to a two-dimensional representation. Methods include simple slices of the network, to more advanced cultural consensus methods.

The chapter further offers an overview of network measures on both the network and node level. Network level measures are covered with the objective to identify appropriate control measures. Node level measures were reviewed to determine the appropriateness of measuring informal social network positions of individuals. Based on the conceptualisation of social position by Borgatti (2005); Everett and Borgatti (2005) the measurements were divided into two groupings: radial and medial measures. Radial measures contain degree and eigenvector centrality, whereas medial measures are variations such as betweenness centrality and closeness centrality.

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7.5 Analysis and Findings

The objective of Chapter 5 is to report on the actual employed methodology. This included the chosen process to reduce the CSS data to a representative criterion for both advice and friendship, which is used to produce the independent variable (SNC acuity), as well as the particular dependent social network position measures and various control measures.

The advice and friendship criterion networks were reduced in different manners. This is because a true relation must employ different assumptions for the different relations. Only through the agreement of both parties, would a friendship relation be recorded as true. Advice relations only rely on the advice seeking party to nominate the relation for it to exist. With the established criterion network, each person's perception is then compared to the criterion using two methods that produces interpersonal acuity and structural acuity.

To determine individual social network position (the dependent variable), the true network was used for node level centrality calculations. The measures of position included degree, betweenness (including proximal target and source betweenness), eigenvector centrality, and constraint.

Various control measures are included to measure the effect of acuity on social positions, and ensure that spurious responses are controlled. The control measures included density, reciprocity, size, hierarchy, centralisation, and transitivity. Formal position was deduced from the individual's organisational hierarchical position. Various control measures were also included to control for spurious responses.

All the variables are subsequently analysed using bivariate analysis, to uncover interactions and correlations between variables in the same class. A key finding at this point of Chapter 5 is that H1a is supported, across all three datasets, for both advice and friendship relations. With an understanding of variable interactions, Chapter 5 then proceeds with highlighting key considerations for regression procedures when working with network data. Steps are taken to reduce multicollinearity in the data.

The final section of the chapter employs multi-relational quadratic assignment procedure, which is a non-parametric linear regression method, to test the two remaining hypotheses. From the regression results, both hypothesis H2b and H3a were supported on both relational dimensions.

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7.6 Discussion

The objective of Chapter 6 is to provide an extended discussion and resolution to the issues highlighted in Chapter 2 (structure vs agency),Chapter 3 (direction of causality and nature of acuity). This is done by formalising the theoretical framework of prior literature, and developing an extended theory that is more congruent with the empirical findings. The extended theory, network theory, is formally defined and contrasted with the taken for granted theoretical lens of prior literature. Networking theory is then placed within increasingly wider and broader contexts, first in social network cognition analysis (SNCA) literature and finally in SNA literature.

Key implications for SNCA are the reversal of the assumed direction of causality, and particularly the role of agency within cognition. Most research has approached SNCA research from the structuralist agenda that usually includes a dulled appreciation for agency within network theory. However, using structuration theory from Giddens (1984), it is shown how agency is important within structural thought. Giddens (1984) highlights a key differentiation between structure and system. System is equated to the actual complex social network, which contains the actual social dynamics, including power, trust, authority, and a range of social relational constructs. Structure is the inferred rules and resources of the larger system held by the individual in memory. Structure is thus reliant on two parameters: the appropriateness of its application, and the extent of its conceptualisation. In other words, for structure to be of help to an individual in a social system, the individual must first apply the correct inferred structure, while retaining enough information of the rules and resources for it to be of aid. Appropriate application of structure within the system recursively reinforces the system. However, those individuals who are competent, knowledgeable, and are capable of applying the structure appropriately, gain agency, which is equatable to power, since it is the ability to change circumstances, such as the system itself. Thus, high SNC acuity is accordingly an appropriate use of information of rules and resources of the social system that unlocks agency for the individual. Such an individual could then change the system, within bounds, to their advantage. Structure is, therefore, maintained within networking theory, but agency is afforded appropriate attention.

Extending the implication to an increasingly wider context, namely SNA, a final model is presented that includes prior research in the investigation of social position. The model highlights the mediating role of motivation and acuity in leading to social network position.

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The model, therefore, offers key insights for future research, since it establishes key links from prior research, only available by reversing the assumed direction of causality between network position and SNC acuity.

7.7 Limitations

The thesis is not without key limitations. This section will highlight the identified limitations of the findings. The limitations are divided into methodological and conceptual limitations. The methodological limitations stem from the methodological choices and the eventual execution. The conceptual limitations stem from the choices of relevant literature and theoretical approaches to the problem. Lastly, there are limitations to the central thesis, due to both the methodological and conceptual choices, which requires further research. Each category will be discussed below.

7.7.1 Conceptual Limitations

The thesis is embedded in SNA and SNCA, since the fields offer applicable theory and tools to investigate how people deal with their social networks. However, there are other options that would be able to contribute to the investigation. For instance, there are key works in transactive memory systems and broader psychology research that could be able to contribute to the investigation and offer more insights.

The thesis greatly reduced the psychological complexity of individuals in favour of gains in interpretability and operationalisation of the research. A full inclusion of psychological perspectives would most certainly aid in improving the conceptual and theoretical approach, but would need a separate effort to provide fair treatment to the application of the field in such an entangled context.

Furthermore, issues within the digital domain of social networks prompt the research, but the actual conceptual and empirical investigation was limited to the analogue domain. The choice has clear implications of the generalisability of the research implications to the digital domain. The findings are limited in only being able to suggest a research agenda and focus that should be applied within the digital domain of networks.

Lastly, the context was delineated to organisational social networks that limits any findings to organisational contexts. Although organisations offer a rich social environment to

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study, there are limitations in the broader implications of any findings.

7.7.2 Methodological Limitations

The methodological choices made throughout the thesis also result in limitations that should be highlighted. First, the choice of datasets is limited in multiple ways. All three datasets are from organisational contexts that were gathered on three separate occasions by three separate research efforts. Different instruments produced the three datasets, particularly the framing of the questions and platform i.e., electronic vs paper. Although this reduces the effect of biases stemming from a single instrument or researcher, it introduces problems of comparability of the datasets. It introduces countless variables, which cannot be controlled for, and thus reduces the confidence and robustness of the findings.

The choice of data gathering instrument—cognitive social structure survey—substantially reduces the practical size of each dataset. These datasets offer a lot of information of each respondent that is useful in triangulating criterion networks. It is, however, limiting in the generalisability of the empirical findings, since the samples are small and errors large.

There were key choices made about the relevant variables and their calculation. *First*, the methodology employed particular centrality measures, yet there are many more measures that can be included. Centrality measures are used as proxy for informal social positions. It is, however, a key assumption that might not hold in all contexts. More nuanced measures of advantageous social position could be used that might include surveying individuals about their actual preferences. The assumption that the chosen centrality measures are preferred positions thus limits the findings. *Second*, key assumptions were made about the reduction methods to establish a criterion network. It is reasonable, yet impractical in this thesis, to utilise different means of defining a criterion network. Explored options include more advanced methods such as iterative reweighing or cultural truth methods such as the Romney-Batchelder method. *Third*, the choice of control measures is also limited to the available measures from the three datasets, and since each dataset was gathered in separate occasions, there could be multiple variables that are not controlled for. For instance, the tenure of each individual is only known in one of the datasets, but would be a key control variable for social network acuity. This limits the findings, through the possibility of unmeasured variables confounding the findings.

Lastly, the choice of statistical method to determine the significance of the relation be-

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tween acuity and social position, carries limitations. Employing multiple relation random assignment procedure (MRQAP), is an attempt to overcome various limitations of normal regression methods on social network data. However, the response variables are not normally distributed that still leaves the method vulnerable to erroneous significance tests (Dekker *et al.*, 2007).

7.7.3 Further research

Based on the findings and the above limitations, it would be prudent to highlight suggestions for future research.

A key part of the thesis is to question the assumption of a direction of causality between network acuity and social position. However, proving direction of causality requires further research such as though methods using longitudinal data and experiments. There is nevertheless evidence and a proposed theoretical model providing impetus to direct such research efforts. Future studies should not, however, naïvely dictate a single direction of causality. The objective is to rather emphasise that social position could be both the antecedent and consequence of social network acuity that is in line with the proposal by Tasselli *et al.* (2015) for uncovering the co-evolution of network and individual, as well as the call from within SNCA to bring the individual back into conceptualisation of social networks (Kilduff and Krackhardt, 1994).

Another key point encouraging further study is the observed interaction between formal social position and social network acuity that could be due to sampling bias. It would be a basic process to measure SNC acuity while considering levels of hierarchy.

From the limitations, there are multiple considerations for future studies, particularly assumptions of applicable variables. The methodology had multiple options, and for execution not all could be considered. This leaves future studies to investigate the difference in findings when considering different criterion networks, or using different proxies for advantageous position. This also encourages gathering more datasets that could include other control variables such as tenure of each respondent.

Lastly, there is great scope to revert attention of SNCA towards the digital domain social networks. This opens up multiple questions. For instance, do social media platforms influence the cognition of personal social networks? Measuring recall of personal networks and comparing it to the individuals digital representation of the network would offer a

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productive research agenda. Comparing people's cognitions, between active and inactive digital social network users, would also improve the understanding of how these platforms interact with analogue network cognition. Does it improve it, change it, or reduce it? Such studies need not be limited to personal networks, since there are professional digital social network platforms that could be investigated in conjunction with professional analogue networks. Moreover, organisational in-house social media platforms are becoming more popular. These platforms offer key opportunities to investigate the interplay between such digital platforms and social network cognition in the analogue domain. For instance, comparing the size and acuity of individual network cognitions between organisations with and without such a platform, would be able to offer key insights into how the digital domain interacts with the analogue.

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CHAPTER A

SNA MEETINGS

TABLE A.1: *Social network analysis meetings in the 1970's.*

Date	Organisers	Some Notable Attendees
June 1972	Harrison White	Steven D. Berkowitz
		Otis & Beverly Duncan
		James A. Davis
		Joel Levine
Spring 1974	H. Russel Bernard	Paul Holland
		Douglas R. White
		Alvin Wolfe
		Patrick Doreian
		Mark Granovetter
		Samuel Leinhardt
		Linton C. Freeman
December 1974-'77	Forrest R. Pitts	Everett M. Rogers
		Lawrence Kincaid
		Brian L. Foster
		John Sonquist
August 1974	Barry & Beverly Wellman	*None on record*
Summer 1975	Samuel Leinhardt and	Dorwin Cartwright
	H. Russel Bernard	Frank Harary
		J. Clyde Mitchell
		John A. Barnes
		Claude Flament
		James A. Davis
		Harrison White
March 1978	Barry Wellman	Steven Berkowitz
		Peter Carrington

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Table A.1 continued from previous page

Date	Organisers	Some Notable Attendees
		Bonnie H. Erickson
		Harriet Friedman
		Nancy Howell
		Lorne Tepperman
		Charles Tilly
		Harrison White
		Patrick Doreian
		Joseph Galaskiewicz
		Samuel Leinhardt
		Joel Levine
		Stanley Wasserman
January 1979	D. Lawrence Kincaid	H. Russell Bernard
		Ronald S. Burt
		Patrick Doreian
		Brian L. Foster
		Sue Freeman
		George Barnett
		Ronald Rice
		Joseph K. Woelfel
		Nancy Pollack
1981	Nan Lin	Peter V. Marsden
		Mark Granovetter
		Edward O. Laumann
		Peter Blau
		Barry Wellman
		Bonnie H. Erickson
		Ronald S. Burt
		James S. Coleman
		Charles Kadushin
		Karen S. Cook

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CHAPTER B

PHARMA QUESTIONNAIRE

To help you interpret the five relations, we offer the following hypothetical scenarios.

- You are celebrating a significant personal milestone. You want to celebrate this milestone with friends and family. Who, from your department, would you invite to the gathering (assuming distance is not a problem)?
- You are struggling to resolve a work-task related issue in your day-to-day work, who would you approach for advice on how resolve the issue?
- You are embarrassed that you do not know something that you should, and you need to confide in someone about it. Who would you feel comfortable approaching?
- You need someone to persuade others to help with a difficult project, that would benefit the organisation. Because the project is strictly not part of formal work requirements, you cannot use rank, or ask someone else to use their higher rank to help you. Who would be able to persuade peers and superiors to help on the project?
- Within your rough area of expertise at the organisation, who would you consider some of the more experienced and knowledgeable people?

Each of these hypothetical scenarios corresponds to a column below. Please indicate the people (shown on the left) that you would select given each hypothetical. The best way is to go down each column in turn and select the person on the left that would best fit the description in the column heading. You do not have to consider every individual, just select those that come to mind first when you consider each scenario.

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LIST OF REFERENCES

ABRAHAM, A., HASSANIEN, A.-E. and SNÁŠEL, V. (2010). *Computational Social Network Analysis: Trends, Tools and Research Advances*. Computer, Communications and Networks. Springer, London.

AIELLO, W., CHUNG, F. and LU, L. (2000). A random graph model for massive graphs. In: *Proceedings of the thirty-second annual ACM symposium on Theory of computing*, pp. 171–180. ACM.

ALBERT, R., JEONG, H. and BARABÁSI, A.-L. (1999). Internet: Diameter of the World-Wide Web. *Nature*, vol. 401, no. 6749, pp. 130–131.

BACKSTROM, L., BOLDI, P., ROSA, M., UGANDER, J. and VIGNA, S. (2012). Four degrees of separation. In: *Proceedings of the 4th Annual ACM Web Science Conference*, pp. 33–42. ACM, Evanston, Illinois, USA.

BALKUNDI, P. and KILDUFF, M.J. (2006). The ties that lead: A social network approach to leadership. *The Leadership Quarterly*, vol. 17, no. 4, pp. 419–439.

BALKUNDI, P., KILDUFF, M.J. and HARRISON, D.A. (2011). Centrality and charisma: Comparing how leader networks and attributions affect team performance. *Journal of Applied Psychology*, vol. 96, no. 6, pp. 1209–1222.

BANKS, D. and CARLEY, K.M. (1994). Metric inference for social networks. *Journal of Classification*, vol. 11, no. 1, pp. 121–149. ISSN 01764268.

BARABÁSI, A.-L. (2002). *Linked: The New Science of Networks*. Perseus Publishing, Cambridge,MA. ISBN 9780738206677.

BARABÁSI, A.-L. and ALBERT, R. (1999). Emergence of Scaling in Random Networks. *Science*, vol. 286, no. 5439, pp. 509–512.

BARNES, J.A. (1954). Class and Committees in a Norwegian Island Parish. *Human Relations*, vol. 7, no. 1, pp. 39–58.

BATCHELDER, W.H., KUMBASAR, E. and BOYD, J.P. (1997). Consensus analysis of three-way social network data. *The Journal of Mathematical Sociology*, vol. 22, no. 1, pp. 29–58.

BERKOWITZ, S.D. (1982). *An Introduction to Structural Analysis: The Network Approach to Social Research*. Butterworth, Toronto, Canada.

Stellenbosch University https://scholar.sun.ac.za

Bernard, H.R. and Killworth, P.D. (1973). On the social structure of an ocean-going research vessel and other important things. *Social Science Research*, vol. 2, no. 2, pp. 145–184.

Bernard, H.R. and Killworth, P.D. (1977). Informant accuracy in social network data II. *Human Communication Research*, vol. 4, no. 1, pp. 3–18.

Bernard, H.R., Killworth, P.D. and Sailer, L. (1979). Informant accuracy in social network data IV: a comparison of clique-level structure in behavioral and cognitive network data. *Social Networks*, vol. 2, no. 3, pp. 191–218.

Bernard, H.R., Killworth, P.D. and Sailer, L. (1982). Informant Accuracy in Social-Network Data V. An Experimental Attempt to Predict Actual Communication from Recall Data. *Social Science Research*, vol. 11, no. 1, pp. 30–66.

Bhagat, S., Burke, M., Diuk, C., Filiz, I.O. and Edunov, S. (2016). Three and a half degrees of seperation.
Available at: `https://research.fb.com/three-and-a-half-degrees-of-separation`

Blau, P.M. (1977). A Macrocosial Theory of Social Structure. *American Journal of Sociology*, vol. 83, no. 1, pp. 26–54.

Bonacich, P. (1987). Power and Centrality: A Family of Measures. *American Journal of Sociology*, vol. 92, no. 5, pp. 1170–1182.

Bonacich, P. (2004). The Invasion of the Physicists. *Social Networks*, vol. 3, no. 26, pp. 285–288.

Bondonio, D. (1998). Predictors of accuracy in perceiving informal social networks. *Social Networks*, vol. 20, no. 4, pp. 301–330.

Borgatti, S.P. (2005). Centrality and network flow. *Social Networks*, vol. 27, no. 1, pp. 55–71.

Borgatti, S.P. (2006). Identifying sets of key players in a social network. *Computational and Mathematical Organization Theory*, vol. 12, no. 1, pp. 21–34.

Borgatti, S.P., Brass, D.J. and Halgin, D.S. (2014). Social network research: confusions, criticisms, and controversies. In: Brass, D., Labianca, G., Mehra, A., Halgin, D. and Borgatti, S.P. (eds.), *Contemporary Perspectives on Organizational Social Networks (Research in the Sociology of Organizations)*, vol. 40, pp. 1–29. Emerald Group Publishing Limited, Bradford, UK.

Borgatti, S.P. and Everett, M.G. (2006). A Graph-theoretic perspective on centrality. *Social Networks*, vol. 28, no. 4, pp. 466–484.

Stellenbosch University https://scholar.sun.ac.za

BORGATTI, S.P. and FOSTER, P.C. (2003). The Network Paradigm in Organizational Research: A Rieview and Typology. *Journal of Management*, vol. 29, no. 6, pp. 991–1013.

BORGATTI, S.P. and HALGIN, D.S. (2011*a*). Consensus Analysis. In: KRONENFELD, D.B., BENNARDO, G., DE MUNCK, V.C. and FISCHER, M.D. (eds.), *A Companion to Cognitive Anthropology*, 1st edn, chap. 10, pp. 171 – 190. Blackwell Publishing, Chichester, West Sussex, UK.

BORGATTI, S.P. and HALGIN, D.S. (2011*b*). On network theory. *Organization Science*, vol. 22, pp. 1168–1181.

BORGATTI, S.P. and LOPEZ-KIDWELL, V. (2011). Network Theory. In: SCOTT, J. and CARRINGTON, P.J. (eds.), *The SAGE Handbook of Social Network Analysis*, chap. 4, pp. 40–54. SAGE Publications, London.

BORGATTI, S.P., MEHRA, A., BRASS, D.J. and LABIANCA, G. (2009). Network analysis in the social sciences. *Science*, vol. 323, no. 5916, pp. 892–895.

BOTT, E. (1971). *Family and social network: Roles, norms and external relationships in ordinary urban families.* 2nd edn. Routledge, Abingdon, Oxon.

BOYD, D.M. and ELLISON, N.B. (2008). Social network sites: Definition, history, and scholarship. *Journal of Computer-Mediated Communication*, vol. 13, no. 1, pp. 210–230.

BRANDES, U. (2001). A faster algorithm for betweenness centrality. *The Journal of Mathematical Sociology*, vol. 25, no. 2, pp. 163–177.

BRANDES, U. (2008). On variants of shortest-path betweenness centraltiy and their generic computation. *Social Networks*, vol. 30, no. 2, pp. 136–145.

BRANDS, R.A. (2013). Cognitive Social Structures in Social Network Analysis: A Review. *Journal of Organizational Behavior*, vol. 34, no. S1, pp. S82–S103.

BRANDS, R.A. and KILDUFF, M.J. (2014). Just Like a Woman? Effects of Gender-Biased Perceptions of Friendship Network Brokerage on Attributions and Performance. *Organization Science*, vol. 25, no. 5, pp. 0–19.

BRANDS, R.A., MENGES, J.I. and KILDUFF, M.J. (2015). The Leader-in-Social-Network Schema: Perceptions of Network Structure Affect Gendered Attributions of Charisma. *Organization Science*, vol. 26, no. 4, pp. 1210–1225.

Stellenbosch University https://scholar.sun.ac.za

Breiger, R.L., Boorman, S.A. and Arabie, P. (1975). An algorithm for clustering relational data with applications to social network analysis and comparison with multidimensional scaling. *Journal of Mathematical Psychology*, vol. 12, no. 3, pp. 328–383.

Burt, R.S. (1980). Models of Network Structure. *Annual Review of Sociologyual Review of Sociology*, vol. 6, no. 1, pp. 79–141.

Burt, R.S. (1982). *Toward a Structural Theory of Action: Network Models of Social Structure, Perception, and Action.* Academic Press, New York, NY.

Burt, R.S. (2000). The network structure of social capital. *Research in Organizational Behavior*, vol. 22, pp. 345–423.

Burt, R.S. (2001). Bandwidth and echo: trust, information, and gossip in social networks. In: Casella, A. and Rauch, J.E. (eds.), *Networks and Markets: Contributions from Economics and Sociology*. Russel Sage Foundation.

Burt, R.S. (2004). Structural Holes and Good Ideas. *American Journal of Sociology*, vol. 110, no. 2, pp. 349–399.

Burt, R.S. (2012). Network-Related Personality and the Agency Question: Multirole Evidence from a Virtual World. *American Journal of Sociology*, vol. 118, no. 3, pp. 543–591.

Burt, R.S., Kilduff, M.J. and Tasselli, S. (2013). Social Network Analysis: Foundations and Frontiers on Advantage. *Annual Review of Psychology*, vol. 64, pp. 527–547.

Burt, S.A. (2008). Genes and Popularity: Evidence of an Evocative Gene-Environment Correlation. *Psychological Science*, vol. 19, no. 2, pp. 112–113.

Butts, C.T. (2008*a*). Social network analysis: A methodological introduction. *Asian Journal of Social Psychology*, vol. 11, no. 1, pp. 13–41.

Butts, C.T. (2008*b*). Social Network Analysis with sna. *Journal of Statistical Software*, vol. 24, no. 6, pp. 1–51.

Butts, C.T. (2016). sna: Tools for Social Network Analysis.
Available at: `https://cran.r-project.org/package=sna`

Butts, C.T. and Carley, K.M. (2001). Multivariate Methods for Inter-Structural Analysis.

Stellenbosch University https://scholar.sun.ac.za

Carley, K.M. (1990). Group Stability: A Socio-Cognitive Approach. In: Lawler, E., Markovsky, B., Ridgeway, C. and Walker, H. (eds.), *Advances in Group Processes: Theory and Research*, vol. 7, vii edn, pp. 1–44. JAI Press, Greenwhich, CN.

Cartwright, D. and Harary, F. (1956). Structural Balance: a generalisation of Heider's theory. *The Psychological Review*, vol. 63, no. 5, pp. 277–293.

Casciaro, T. (1998). Seeing things clearly: social structure, personality, and accuracy in social network perception. *Social Networks*, vol. 20, no. 4, pp. 331–351.

Casciaro, T., Carley, K.M. and Krackhardt, D. (1999). Positive Affectivity and Accuracy in Social Network Perception. *Motivation and Emotion*, vol. 23, no. 4, pp. 285–306.

Casciaro, T., Gino, F. and Kouchaki, M. (2014). The Contaminating Effects of Building Instrumental Ties: How Networking Can Make Us Feel Dirty. *Administrative Science Quarterly*, vol. 59, no. 4, pp. 705–735.

Christakis, N.A. and Fowler, J.H. (2007). The Spread of Obesity in a Large Social Network over 32 Years. *New England Journal of Medicine*, vol. 357, no. 4, pp. 370–379.

Christakis, N.A. and Fowler, J.H. (2008). The collective dynamics of smoking in a large social network. *New England journal of medicine*, vol. 358, no. 21, pp. 2249–2258.

Coleman, J.S., Katz, E. and Menzel, H. (1957). The diffusion of an innovation among physicians. *Sociometry*, vol. 20, no. 4, pp. 253–270.

Coleman, J.S. and Macrae, D. (1960). Electronic Processing of Sociometric Data for Groups up to 1,000 in Size. *American Sociological Review*, vol. 25, no. 5, pp. 722–727.

Cranmer, S.J., Ohio, T., Leifeld, P., Eth, E., Mcclurg, S.D. and Rolfe, M. (2017). Navigating the Range of Statistical Tools for Inferential Network Analysis. *American Journal of Political Science*, vol. 61, no. 1, pp. 237–251. ISSN 00925853.

Csardi, G. and Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal*, vol. Complex Sy, p. 1695.
Available at: `http://igraph.org`

Davis, J.A. (1967). Clustering and structural balance in graphs. *Human Relations*, vol. 20, no. 2, pp. 181–187.

Stellenbosch University https://scholar.sun.ac.za

De Lange, D., Agneessens, F. and Waege, H. (2004). Asking Social Network Questions: A Quality Assessment of Different Measures. *Metodološki zvezki*, vol. 1, no. 2, pp. 351–378.

De Soto, C.B. (1960). Learning a social structure. *Journal of abnormal and social psychology*, vol. 60, no. 3, pp. 417–421.

De Soto, C.B. and Bosley, J.J. (1962). The cognitive structure of a social structure. *Journal of Abnormal and Social Psychology*, vol. 64, no. 30, pp. 3–307.

Dekker, D., Krackhardt, D. and Snijders, T.A. (2007). Sensitivity of MRQAP tests to collinearity and autocorrelation conditions. *Psychometrika*, vol. 72, no. 4, pp. 563–581.

Del Vicario, M., Bessi, A., Zollo, F., Petroni, F., Scala, A., Caldarelli, G., Stanley, H.E. and Quattrociocchi, W. (2016). The spreading of misinformation online. *Proceedings of the National Academy of Sciences*, vol. 113, no. 3, pp. 554–559.

Dessí, R., Gallo, E. and Goyal, S. (2016). Network cognition. *Journal of Economic Behavior and Organization*, vol. 123, pp. 78–96.

Dijkstra, E.W. (1959). A note on two problems in connexion with graphs. *Numerische Mathematik*, vol. 1, no. 1, pp. 269–271.

Dunbar, R.I.M. (1998). The Social Brain Hypothesis. *Evolutionary Anthropology*, vol. 6, no. 5, pp. 178–190.

Durkheim, E. (1982). *The Rules of Sociological Method*. 1st edn. The Free Press, New York.

Eisenhardt, K.M. (1989). Agency Theory: An Assessment and Review. *Academy of Management Review*, vol. 14, no. 1, pp. 57–74.

Erdös, P. and Rényi, A. (1959). On Random Graphs. *Publicationes Mathematicae*, vol. 6, pp. 290–297.

Everett, M.G. and Borgatti, S.P. (2005). Extending Centrality. In: Carrington, P.J., Scott, J. and Wasserman, S. (eds.), *Models and Methods in Social Network Analysis*, chap. 4, pp. 57–76. Cambridge University Press, New York.

Everett, M.G. and Krackhardt, D. (2012). A second look at Krackhardt's graph theoretical dimensions of informal organizations. *Social Networks*, vol. 34, no. 2, pp. 159–163.

Faloutsos, M., Faloutsos, P. and Faloutsos, C. (1999). On power-law relationships of the Internet topology. In: *ACM SIGCOMM Computer Communication Review*, vol. 29, pp. 251–262.

Stellenbosch University https://scholar.sun.ac.za

Ferguson, N. (2017). The False Prophecy of Hyperconnection: How to Survive the Networked Age. *Foreign Affairs*, vol. 96, no. 68, pp. 8–23.

Flament, C. (1963). *Applications of Graph Theory to Group Structure.* Mathematical Analysis of Social Behavior. Prentice Hall, New Jersey.

Flynn, F.J., Reagans, R.E., Amanatullah, E.T. and Ames, D.R. (2006). Helping one's way to the top: Self-monitors achieve status by helping others and knowing who helps whom. *Journal of personality and social psychology*, vol. 91, no. 6, pp. 1123–37.

Flynn, F.J., Reagans, R.E. and Guillory, L. (2010). Do you two know each other? Transitivity, homophily, and the need for (network) closure. *Journal of Personality and Social Psychology*, vol. 99, no. 5, pp. 855–869.

Fragale, A.R., Overbeck, J.R. and Neale, M.A. (2011). Resources versus respect: Social judgments based on targets' power and status positions. *Journal of Experimental Social Psychology*, vol. 47, no. 4, pp. 767–775.

Freeman, L.C. (1979). Centrality in Social Networks Conceptual Clarification. *Social Networks*, vol. 1, pp. 215–239.

Freeman, L.C. (1992). Filling in the Blanks: A Theory of Cognitive Categories and the Structure of Social Affiliation. *Social Psychology Quarterly*, vol. 55, no. 2, pp. 118–127.

Freeman, L.C. (2004). *The development of social network analysis: A study in the sociology of science.* Empirical Press, Vancouver.

Freeman, L.C. (2008). Going the Wrong Way on a One-Way Street: Centrality in Physics and Biology. *Journal of Social Structure*, vol. 9, no. 2, pp. 1–15.

Freeman, L.C. (2011). The Development of Social Network Analysis-with an emphasis on recent events. In: Scott, J. and Carrington, P.J. (eds.), *The SAGE handbook of social network analysis*, chap. 3, pp. 26–39. SAGE Publications, London.

Freeman, L.C. and Romney, A.K. (1987). Words, deeds, and social structure: A preliminary study of the reliability of informants. *Human Organization*, vol. 46, no. 4, pp. 330–334.

Freeman, L.C., Romney, A.K. and Freeman, S.C. (1987). Cognitive Structure of Informant Accuracy. *American Anthropologist, New Series*, vol. 89, no. 2, pp. 310–325.

Stellenbosch University https://scholar.sun.ac.za

Gibson, C., Hardy, J.H. and Buckley, M.R. (2014). Understanding the role of networking in organizations. *Career Development International*, vol. 19, no. 2, pp. 146–161.

Giddens, A. (1984). *The Constitution of Society: Outline of the Theory of Structuration*. Polity Press, Oxford.

Granovetter, M.S. (1973). The Strength of Weak Ties. *American Journal of Sociology*, vol. 78, no. 6, pp. 1360–1380.

Grippa, F. and Gloor, P.A. (2009). You are who remembers you. Detecting leadership through accuracy of recall. *Social Networks*, vol. 31, no. 4, pp. 255–261.

Guetzkow, H. and Simon, H.A. (1955). The impact of certain communication netw upon organization and performance in task-oriented groups. *Management Science*, vol. 1, no. 3, pp. 233–250.

Hahl, O., Kacperczyk, A.O. and Davis, J.P. (2016). Knowledge asymmetry and brokerage: Linking network perception to position in structural holes. *Strategic Organization*, vol. 14, no. 2, pp. 118–143.

Haines, V.a. (1988). Social network analysis, structuration theory and the holism-individualism debate. *Social Networks*, vol. 10, no. 2, pp. 157–182.

Handcock, M.S., Hunter, D.R., Butts, C.T., Goodreau, S.M., Krivitsky, P.N., Bender-deMoll, S. and Morris, M. (2016). statnet: Software Tools for the Statistical Analysis of Network Data.
Available at: `CRAN.R-project.org/package=statnet`

Harary, F., Norman, R.Z. and Cartwright, D. (1965). *Structural Models: an introduction to the theory of directed graphs*. Wiley, New York.

Heald, M.R., Contractor, N.S., Koehly, L.M. and Wasserman, S. (1998). Formal and emergent predictors of coworkers' perceptual congruence on an organization's social structure. *Human Communication Research*, vol. 24, no. 4, pp. 536–563.

Heider, F. (1946). Attitudes and cognitive organization. *The Journal of psychology*, vol. 21, no. 1, pp. 107–112.

Heilbroner, R.L. (1953). *The worldly philosophers : the lives, times, and ideas of the great economic thinkers*. 7th edn. Touchstone, New York, NY.

Stellenbosch University https://scholar.sun.ac.za

Ho, V.T. and Sze-Sze, W. (2009). Knowing who knows what and who knows whom: Expertise recognition, network recognition, and individual work performance. *Journal of Occupational & Organizational Psychology*, vol. 82, no. 1, pp. 147–158.

Huisman, M. and Van Duijn, M.A.J. (2011). A Readers Guide To SNA Software. In: Scott, J. and Carrington, P.J. (eds.), *The SAGE Handbook of Social Network Analysis*, chap. 38, pp. 578–600. SAGE Publications, London.

Ibarra, H. and Andrews, S.B. (1993). Power, Social Influence, and Sense Making: Effects of Network Centrality and Proximity on Employee Perceptions. *Administrative Science Quarterly*, vol. 38, no. 2, pp. 277–303.

Ingram, P. and Morris, M.W. (2007). Do People Mix at Mixers? Homophily , and the "Life of the Party". *Administrative Science Quarterly*, vol. 52, pp. 558–585.

James, G., Witten, D., Hastie, T. and Tibshirani, R. (2013). *An introduction to Statistical Learning: with applications in R*. Springer, New York, NY.

Janicik, G.A. and Larrick, R.P. (2005). Social network schemas and the learning of incomplete networks. *Journal of personality and social psychology*, vol. 88, no. 2, pp. 348–364.

Kabacoff, R.I. (2015). *R in Action: Data analysis and graphics with R*. 2nd edn. Manning, Shelter Island, NY.

Kadushin, C. (1966). The Friends and Supporters of Psychotherapy: on social circles in urban life. *American sociological review*, vol. 31, no. 6, pp. 786–802.

Karinthy, F. (1929). Chain-Links. In: Newman, M.E.J., Barabási, A.-L. and Watts, D.J. (eds.), *The Structure and Dynamics of Networks*, pp. 21–26. Princeton University Press, Princeton.

Katz, E. and Lazarsfeld, P.F. (1955). *Personal Influence, The part played by people in the flow of mass communications*. Free Press, New York.

Katz, L. (1953). A new status index derived from sociometric analysis. *Psychometrika*, vol. 18, no. 1, pp. 39–43.

Kilduff, M.J., Crossland, C., Tsai, W. and Krackhardt, D. (2008). Organizational network perceptions versus reality: A small world after all? *Organizational Behavior and Human Decision Processes*, vol. 107, no. 1, pp. 15–28.

Stellenbosch University https://scholar.sun.ac.za

Kilduff, M.J. and Krackhardt, D. (1994). Bringing the Individual Back in: A Structural Analysis of the Internal Market for Reputation in Organizations. *The Academy of Management Journal*, vol. 37, no. 1, pp. 87–108.

Kilduff, M.J. and Krackhardt, D. (2008). *Interpersonal Networks In Organizations: Cognition, Personality, Dynamics, and Culture*. Structural Analysis in The Social Sciences. Cambridge University Press, New York.

Killworth, P.D. and Bernard, H.R. (1976). Informant Accuracy in Social Network Data. *Human Organization*, vol. 35, no. 3, p. 269.

Killworth, P.D. and Bernard, H.R. (1979). Informant accuracy in social network data III: A comparison of triadic structure in behavioral and cognitive data. *Social Networks*, vol. 80, no. 1, pp. 10–46.

Koehly, L.M. and Pattison, P.E. (2005). Random Graph Models for Social Networks: Multiple Relations or Multiple Raters. In: Carrington, P.J., Scott, J. and Wasserman, S. (eds.), *Models and Methods in Social Network Analysis*, chap. 9, pp. 162–191. Cambridge University Press, New York, NY.

Koskinen, J. (2004). Model Selection for Cognitive Social Structures. Tech. Rep., Stockholm Univerity, Department of Statistics, Stokholm.

Krackhardt, D. (1987*a*). Cognitive Social Structures. *Social Networks*, vol. 9, no. 1, pp. 109–134.

Krackhardt, D. (1987*b*). QAP Partialing as a Test of Spuriousness. *Social Networks*, vol. 9, no. 1, pp. 171–186.

Krackhardt, D. (1990). Assessing the Political Landscape: Structure, Cognition, and Power in Organizations. *Administrative Science Quarterly*, vol. 35, no. 2, pp. 342–369.

Krackhardt, D. (1992). The Strength of Strong Ties: The importance of Philos in Organis zations. In: Nohria, N. and Eccles, R. (eds.), *Networks and Organizations: Structures, Form and Action*, chap. 8, pp. pp. 216–239. Harvard Business School Press, Boston, MA.

Krackhardt, D. (1994). Graph theoretical dimensions of informal organizations. In: Carley, K.M. and Prietula, M. (eds.), *Computational organization theory*, chap. 5, pp. 89–111. Lawrence Erlbaum Associates Publishers, Hillsdale, New Jersey.

Stellenbosch University https://scholar.sun.ac.za

Krackhardt, D. and Kilduff, M.J. (1999). Whether Close or Far: Social Distance Effects on Perceived Balance in Friendship Networks. *Journal of Personality and Social Psychology*, vol. 76, no. 5, pp. 770–782.

Krackhardt, D. and Kilduff, M.J. (2002). Structure, Culture and Simmelian Ties in Entrepreneurial Firms. *Social Networks*, vol. 24, pp. 279–290.

Kumbasar, E., Romney, A.K. and Batchelder, W.H. (1994). Systematic Biases in Social Perception. *American Journal of Sociology*, vol. 100, no. 2, pp. 477–505.

Kuwabara, K.K., Hildebrand, C. and Zou, X. (2018). Lay Theories of Networking: How Laypeople's Beliefs about Networks Affect Their Attitudes and Engagement toward Instrumental Networking. *Academy of Management Review*, vol. 43, no. 1, pp. 50–64.

Landherr, A., Friedl, B. and Heidemann, J. (2010). A Critical Review of Centrality Measures in Social Networks. *Business & Information Systems Engineering*, vol. 2, no. 6, pp. 371–385.

Laumann, E.O. and Guttman, L. (1966). The relative associational contiguity of occupations in an urban setting. *American Sociological Review*, vol. 31, no. 2, pp. 169–178.

Lin, N. (1999). Building a Network Theory of Social Capital. *Connections*, vol. 22, no. 1, pp. 28–51.

Lorrain, F. and White, H.C. (1971). Structural equivalence of individuals in social networks. *The Journal of Mathematical Sociology*, vol. 1, no. 1, pp. 49–80.

Marcum, C.S., Lienert, J., Goldring, M., Lin, J., Miggins, A., Moss, M., Song, S., Thakur, H. and Koehly, L.M. (2017). Ego-Centered Cognitive Social Structures of Close Personal Networks in the United States.
Available at: `https://doi.org/10.31235/osf.io/pg3yx`

Marin, A. and Wellman, B. (2011). Social Network Analysis: an introduction. In: Scott, J. and Carrington, P.J. (eds.), *The SAGE Handbook of Social Network Analysis*, chap. 2, pp. 11–25. SAGE Publications, London.

Marineau, J.E. (2017). Trust and Distrust Network Accuracy and Career Advancement in an Organization. *Group & Organization Management*, vol. 42, no. 4, pp. 487–520.

Mcpherson, J.M. and Ranger-Moore, J.R. (1991). Evolution on a dancing landscape: Organizations and networks in dynamic blau space. *Social Forces*, vol. 70, no. 1, pp. 19–42.

Stellenbosch University https://scholar.sun.ac.za

Mehra, A., Borgatti, S.P., Soltis, S., Floyd, T., Halgin, D.S., Ofem, B. and Lopez-Kidwell, V. (2014*a*). Imaginary Worlds: Using Visual Network Scales to Capture Perceptions of Social Networks. *Contemporary Perspectives on Organizational Social Networks Research in the Sociology of Organizations*, vol. 40, pp. 311–332.

Mehra, A., Kilduff, M.J. and Brass, Daniel, J. (2014*b*). The Social Networks of High and Low Self- monitors : Implications for Workplace Performance. *Administrative Science Quarterly*, vol. 46, no. 1, pp. 121–146.

Menon, T. and Smith, E.B. (2014). Identities in flux: Cognitive network activation in times of change. *Social Science Research*, vol. 45, pp. 117–130.

Menzel, H. and Katz, E. (1955). Social Relations and Innovation in the Medical Profession: The Epidemiology of a New Drug. *Public Opinion Quarterly*, vol. 19, no. 4, p. 337.

Merton, R.K. (1968). The Matthew Effect in Science. *Science*, vol. 159, no. 3810, pp. 56–63.

Milgram, S. (1967). The small world problem. *Psychology Today*, vol. 1, no. 1, pp. 61–66.

Mitchell, J.C. (ed.) (1969). *Social networks in urban situations: analyses of personal relationships in Central African towns*. Manchester University Press, Manchester.

Mizruchi, M.S. and Potts, B.B. (1998). Centrality and power revisited: actor success in group decision making. *Social Networks*, vol. 20, pp. 353–387.

Nadel, S.F. (1957). *The theory of social structure*. London: Cohen & West, London.

Neal, J.W., Neal, Z.P. and Cappella, E. (2016). Seeing and being seen: Predictors of accurate perceptions about classmates' relationships. *Social Networks*, vol. 44, pp. 1–8.

Newman, M., Barabási, A.-L. and Watts, D.J. (eds.) (2006). *The Structure and Dynamics of Networks*. Princeton University Press, Princeton.

Newman, M.E.J. (2010). *Networks: An Introduction*. Oxford University Press, New York, NY.

Oh, H. and Kilduff, M.J. (2008). The Ripple Effect of Personality on Social Structure: Self-Monitoring Origins of Network Brokerage. *Journal of Applied Psychology*, vol. 93, no. 5, pp. 1155–1164.

Ouellette, D.M. (2008). *Shadows on the Cave Wall: The Cognitive Accuracy of Social Network Perception*. D(Phil), Virginia Commonweaelth University.

Stellenbosch University https://scholar.sun.ac.za

Pattison, P.E. (1993). *Algebraic models for social networks Structural analysis in the social sciences*. Structural analysis in the social sciences 7. Cambridge University Press, Cambridge.

Pattison, P.E. (1994). Social cognition in context: some applications of social network analysis. In: Wasserman, S. and Galaskiewicz, J. (eds.), *SAGE Focus Editions: Advances in social network analysis: Research in the social and behavioral sciences*, chap. 4, pp. 79–110. SAGE Publications, Inc., Thousand Oaks, California.

Pool, I.d.S. and Kochen, M. (1978). Contacts and influence. *Social Networks*, vol. 1, pp. 5–51.

Porter, C.M. and Woo, S.E. (2015). Untangling the Networking Phenomenon: A Dynamic Psychological Perspective on How and Why People Network. *Journal of Management*, vol. 41, no. 5, pp. 1477–1500.

Prell, C. (2012). *Social Network Analysis: History, Theory and Methodology*. SAGE Publications, Los Angeles.

Rainie, L. and Wellman, B. (2012). *Networking: The New Social Operating System*. January. MIT Press, Cambridge, MA.

Rees, R. (1985). The Theory of Principal and Agent Part I. *Bulletin of Economic Research*, vol. 37, no. 1, pp. 3–26.

Rogers, E.M. (1962). *Diffusion of innovations*. 3rd edn. The Free Press, New York.

Romney, A.K. and Faust, K. (1982). Predicting the structure of a communications network from recalled data. *Social Networks*, vol. 4, no. 4, pp. 285–304.

Romney, A.K., Weller, S.C. and Batchelder, W.H. (1986). Culture as Consensus: A Theory of Culture and Informant Accuracy. *American Anthropologist*, vol. 88, no. 2, pp. 313–338.

Sabidussi, G. (1966). The Centrality Index Of A Graph. *Psychometrika*, vol. 31, no. 4, pp. 581–603.

Sasovova, Z., Mehra, A., Borgatti, S.P. and Schippers, M.C. (2010). Network Churn: The Effects of Self-Monitoring Personality on Brokerage Dynamics. *Administrative Science Quarterly*, vol. 55, pp. 639–670.

Scott, J. (2000). *Social Network Analysis: A Handbook*. 2nd edn. Sage Publications, London.

Shea, C.T. and Fitzsimons, G.M. (2016). Personal goal pursuit as an antecedent to social network structure. *Organizational Behavior and Human Decision Processes*, vol. 137, pp. 45–57.

Stellenbosch University https://scholar.sun.ac.za

Siciliano, M.D., Yenigün, D. and Ertan, G. (2012). Estimating network structure via random sampling: Cognitive social structures and the adaptive threshold method. *Social Networks*, vol. 34, no. 4, pp. 585–600.

Simmel, G. (1950). *The Sociology of Georg Simmel.* Free Press, Glencoe, Illinois.

Simmel, G. (1971). *Georg Simmel: On Individuality and Social Forms.* The Heritage of Sociology. The University of Chicago Press, Chicago.

Simpson, B. and Borch, C. (2005). Does Power Affect Perception in Social Networks? Two Arguments and an Experimental Test. *Social Psychology Quarterly*, vol. 68, no. 3, pp. 278–287.

Simpson, B., Markovsky, B. and Steketee, M. (2011*a*). Network knowledge and the use of power. *Social Networks*, vol. 33, no. 2, pp. 172–176.

Simpson, B., Markovsky, B. and Steketee, M. (2011*b*). Power and the perception of social networks. *Social Networks*, vol. 33, no. 2, pp. 166–171.

Smith, E.B., Menon, T. and Thompson, L. (2012). Status differences in the cognitive activation of social networks. *Organization Science*, vol. 23, no. 1, p. 67.

Social Media Hat (2015). Social Media Active Users by Network.
Available at: http://www.thesocialmediahat.com/active-users

Song, M.-k., Lin, F.-c., Ward, S.E. and Fine, J.P. (2013). Composite variables. *Nursing research*, vol. 62, no. 1, p. 99.

Sparrowe, R.T., Linden, S.J.W. and Kraimer, M.L. (2001). Social Networks and the Performance of Individuals and Groups. *The Academy of Management Journal*, vol. 44, no. 2, pp. 316–325.

Sunstein, C.R. (2017). *#Republic: Divided democracy in the age of social media.* Princeton University Press, Princeton, New Jersey.

Tamarit, I., Cuesta, J.A., Dunbar, R.I.M. and Sánchez, A. (2018). Cognitive resource allocation determines the organization of personal networks. *Proceedings of the National Academy of Sciences*.

Tasselli, S., Kilduff, M.J. and Menges, J.I. (2015). The microfoundations of organizational social networks: A review and an agenda for future research. *Journal of Management*, vol. 41, no. 5, pp. 1361–1387.

Stellenbosch University https://scholar.sun.ac.za

Thomson-Reuters (2014). Stanford scholars among the most cited. Available at: goo.gl/PGoiXh

Valente, T.W., Coronges, K., Lakon, C. and Costenbader, E. (2008). How Correlated Are Network Centrality Measures? *Connect (Tor)*, vol. 28, no. 1, pp. 16–26.

Wasserman, S. and Faust, K. (1994). *Social Network Analysis: Methods and Applications*. Structural Analysis In The Social Sciences, 1st edn. Cambridge University Press, New York.

Watts, D.J. (1999). *Small Worlds: The Dynamics of Networks between Order and Randomness*. Princeton University Press, Princeton.

Watts, D.J. (2003). *Six Degrees: The Science of a Connected Age*. WW Norton and Company, New York, NY.

Watts, D.J. and Strogatz, S.H. (1998). Collective dynamics of small-world networks. *Nature*, vol. 393, no. June, pp. 440–442.

Wellman, B. (2000). Networking Network Analysts: How INSNA (the International Network for Social Network Analysis) Came to Be. *Connections*, vol. 23, no. 1, pp. 20–31.

Wellman, B., Haase, A.Q., Witte, J. and Hampton, K. (2001). Does the Internet Increase, Decrease, or Supplement Social Capital? *American Behavioral Scientist*, vol. 45, no. 3, pp. 436–455.

Westrum, R. (1978). Science and Social Intelligence about Anomalies: The Case of Meteorites Author. *Social Studies of Science*, vol. 8, no. 4, pp. 461–493.

Westrum, R. (1982). Social Intelligence About Hidden Events. *Knowledge: Creation, Diffusion, Utilization*, vol. 3, no. 3, pp. 381–400.

Wolfe, A.W. (1978). The rise of network thinking in anthropology. *Social Networks*, vol. 1, pp. 53–64.

Yenigün, D., Ertan, G. and Siciliano, M.D. (2017). Omission and commission errors in network cognition and network estimation using ROC curve. *Social Networks*, vol. 50, pp. 26–34.